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Women's Career in the U. S. Federal Government: Wage, Promotion, Leave and Fertility

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WOMEN'S CAREER IN THE U. S. FEDERAL GOVERNMENT: WAGE, PROMOTION, LEAVE AND FERTILITY

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Abstract

This dissertation investigates female career progress in the U. S. federal government in aspects of wage, promotion, leave, and fertility. It sheds lights on how women face trade-offs between career and fertility and how the gender decomposition of supervisors affects gender wage and promotion gaps.

The first chapter examines how female leadership affects the gender wage gap in the U. S. federal government. Using a unique dataset from the Office of Personnel Management, I track careers of civilian employees from 1988 to 2011. I find that in offices where all supervisors are men, male wages are on average 10.6% higher than female wages. In contrast, in offices where all supervisors are women, the wage gap in favor of men disappears and becomes 3.2% in favor of women due to a 7.1% increase in female wages and a 6.7% decline in male wages. Also, the gender of an executive (a higher level supervisor) has a lesser impact on wages than the gender of regular supervisors. However, the gender of an executive has a greater impact on wages of supervisors than on wages of non-supervisors, which is consistent with the theory of mentorship. I account for potential endogeneity caused by a non-random assignment of supervisors by using office fixed effects and an instrumental variable based on retirement. Finally, I investigate potential mechanisms by examining promotions, exits, starting, and exiting positions.

The second chapter examines the effects of the Family Medical Leave Act (FMLA) on the promotion of women into managerial positions using the Office of Personnel Management (OPM) data and imputed fertility rates from Centers for Disease Control and Prevention (CDC) data. I find that after the FMLA was passed in 1993, there was a significant change in the relationship between fertility and promotion, with fertility becoming more negatively associated with promotion. Compared to the relationship prior to 1993, a 10% increase in fertility is associated with an additional 1.3% decline in the probability of being promoted. This suggests that the FMLA may have inhibited the relative career progress of women in high-fertility demographic groups in the U.S. federal civil service system.

The third chapter examines the effect of Medicaid expansion on the fertility rate using individual level panel data under an alternative insurance. We find that without controlling for an alternative insurance, Medicaid eligibility expansion has no significant effect on female fertility. However, we find that for those females not covered by insurance, Medicaid eligibility increases fertility by 5 percentage points per year over time. Such effect is both statistical and economically significant and is stronger among groups of females that are un-married or not employed. These evidence suggests that Medicaid program as a social benefit is more effective for those who need it the most.

Dedication

This dissertation is dedicated to my father Dr. Victor Droganov, who always believes in me, pushes me to the limit, and encourages me to pursue my passion, and to my husband Dr. Bingzhi Zhao whose unconditional love and support kept me going forward during my PhD years.

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Table of Contents

List of Tables

List of Figures

Chapter 1

Women Working for Women: Career Advancement and the Gender Wage Gap in the U. S. Federal Government

Summary This paper investigates how female leadership affects the gender wage gap in the U. S. federal government. Using a unique dataset from the Office of Personnel Management, I track careers of civilian employees from 1988 to 2011. I find that in offices where all supervisors are men, male wages are on average 10.6% higher than female wages. In contrast, in offices where all supervisors are women, the wage gap in favor of men disappears and becomes 3.2% in favor of women due to a 7.1% increase in female wages and a 6.7% decline in male wages. Also, the gender of an executive (a higher level supervisor) has a lesser impact on wages than the gender of regular supervisors. However, the gender of an executive has a greater impact on wages of supervisors than on wages of non-supervisors, which is consistent with the theory of mentorship. I account for potential endogeneity caused by a non-random assignment of supervisors by using office fixed effects and an instrumental variable based on retirement. Finally, I investigate potential mechanisms by examining promotions, exits, starting, and exiting positions.[1]

Keywords: Female leadership, wage gap, instrumental variables, mentorship

JEL Classification: J16, J31

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1.1 Introduction

A persistent, though shrinking, gender wage gap[2] has been documented by a large literature in labor economics. According to the study in Blau and Kahn (2016a), women in the private sector earned 8.4% less than men in 2010,[3] controlling for differences in individual and occupational characteristics, and are less represented among upper-level executive positions[4]. Although the U. S. federal government is considered less discriminatory than the private sector, Bolton and de Figueiredo (2017) record that men are paid significantly more than women in the federal government. Specifically, after controlling for human capital and other factors they show that the wage gap in the public sector decreased from 6.5% in 1988 to 4.9% in 2011. During the same period, I find that the percentage of supervisors who are female increased from 27% to 42% in the public sector. Could the greater representation of women in supervisory and executive positions contribute to the reduction in the wage and promotion gaps in the U. S. federal government? The answer to this question has important policy implications such as if the wage gap could be reduced by imposing gender quotas on leadership.

This study uses a massive dataset from the United States Office of Personnel Management (OPM), which follows over three million civilian federal government employees over a 24-year period, to answer the question whether female leadership helps to reduce wage and promotion gaps in federal government offices. I find that female leadership significantly increases female workers' wages, while simultaneously decreasing male workers' wages, thereby reducing the gender wage gap. In particular, moving an office from all male to all female leadership increases next period female workers' wages in real terms by 7.1%, decreases male workers' wages by 6.7%, thereby reducing the gender pay gap from 10.6% into a reverse gender gap of 3.2%. In this estimation, I control for human capital, race, tenure, occupation category and other fixed effects. To account for the endogeneity possibly caused by the non-random assignments of supervisors to offices, I include office fixed effects into the analysis and I build an instrumental variable based on retirement.

To the best of my knowledge, this is the first paper to analyze how female leadership in-

[2]The gender wage gap is defined as the average yearly earnings of men minus that of women.

[3]Women also suffer more when it comes to bad firm performances. For example, female executives are more exposed to bad firm performances according to Albanesi, Olivetti, and Prados (2015); Asch, Haider, and Zissimopoulos (2005); Belley, Havet, and Lacroix (2015), and female workers suffer larger losses when displaced due to plant closure according to Tate and Yang (2015).

[4]For example, only 6% of U. S. corporate chief executive officers (CEO) and top executive positions were women in 2010 (Matsa and Miller (2011)).

fluences the gender pay gap in the U. S. federal government. The related literature focuses on the private sector. I show that female supervisors and executives reduce gender wage gap in the federal government. Moreover, the existing literature on the direction and the significance of the relationship between the gender wage gap and the gender of the supervisor is inconclusive. While some studies also found that female leadership reduces the wages gap, others found an opposite effect or no effect. For example, Gagliarducci and Paserman (2015), using German industry data, document that the share of females in the top management has an insignificant effect on both male and female wages. In contrast, Cohen and Huffman (2007), using a dataset drawn from the U. S. 2000 Census, find that increased representation of women in management decreases the gender pay gap. However, Maume and Ruppanner (2015), using the American National Study of the Changing Workforce, show that both women and men under a female supervisor earn lower wages on average compared to having a male supervisor. Penner, Toro-Tulla, and Huffman (2012), using private data from an American grocery retailer, find that the gender of the immediate manager has no effect on male and female wages. Bell (2005), using Standard and Poor's ExecuComp, finds that female executives in female-led firms earn 15%-20% higher compensation than women in other firms, and male executives under a female CEO earn less compensation than men in male-led firms.

One of the advantages of the data I use is that I observe the entire population of civilian federal employees from 1988 to 2011. While the related studies use not an entire sample but subsamples to answer how the gender of an executive or supervisors affects the male and female wages, this study conducts the initial analysis based on the 10-percent subsample and then compares the results to the findings from the full sample. I show that the magnitudes from the above results are quite different due to the attenuation bias in the small sample. For example, in the 10-percent sample, the female leadership has no effect on male and female promotions; while using the entire sample, I find that females are more likely to be promoted under female supervisors than under male supervisors. Since previous studies used different data and different data have different attenuation biases, it could be one of the reasons why the literature does not agree.

By utilizing the structure of the OPM dataset, in particular, that it follows careers of all employees from 2008-2011, I furthermore contribute to the literature by explaining the mechanisms through which female leadership affects female wages. Previous studies, using various country data and various private industry data, once again provide mixed results. For example, Bell, Smith, Smith, Verner, et al. (2008), using Danish firm-level data, find that women in women-led firms have a higher probability of promotion, while the percentage of female directors have no effect on promotions of men. However, Maume (2011), using the American National Study of the Changing Workforce data, finds that a female supervisor has a negative impact on female advancement opportunity and positive impact on male advancement opportunity. Blau and DeVaro (2007), by using American Multi-City of Urban Inequality employer survey, find that the gender of an immediate supervisor has no effect on both male and female promotions. Finally, Giuliano, Leonard, and Levine (2005) using data from a large U. S. retail employer, find employees with different-sex managers have on average 3-5% higher quit rates, 3-8% higher dismissal rates, and 8-11% lower promotion rates. By using the full-time employees, I find that under female leadership, females are more likely to be ever promoted from a non-supervisory position to a supervisory position. By restricting the sample to the employees on the General Schedule pay, I find that under female leadership female are more likely to start on a higher grade-step position than under male leadership and more likely to be promoted to a higher grade. Also, under female leadership, male employees have higher propensity to exit the job than under male leadership and the effect is not significant for females.

The rest of the paper is organized as follows: section 3.2 presents the OPM data and discusses the variables construction methods; section 3.3 discusses the benchmark model, explores various approaches to tackle the potential endogeneity, and establishes the main results that female leadership increases female pay and decreases male pay, thereby reduces the gender wage gap in the government sector; section 3.4 investigates further the channels through which the female leadership impacts workers' wages by exploring the effect on workers' career mobility; section 3.5 discusses the potential theoretical explanation for this empirical result; section 3.6 is a robustness check and section 1.7 concludes. Additional tables are included in the Appendix.

1.2 Data and Variables

1.2.1 Data

In this paper, I use the restricted dataset from the United States Office of Personnel Management (OPM). According to Bolton and de Figueiredo (2017), this dataset covers personal records of all non-department-of-defense employees by the U. S. federal government over a 24-year period of 1988-2011. This dataset is the largest of its kind and has a considerably larger scope than any other public release from the OPM. There are over three million unique full-time, non-seasonal employees in over 20 million observations in the data. Since the data is both cross-sectional and longitudinal, at one-year intervals, it allows the researcher to link individuals and their career progressions over time to examine the effect of the gender of executives and supervisors on the wage gap. It contains information on employee careers such wages, work schedules, awards earned, supervisory status, occupation, and their individual characteristics such as gender, race, age, educational background, geographic location, etc. With this dataset, I can focus the empirical analysis in granular detail without concerns about sampling errors. I am also able to generate substantially more power from the statistical tests and conduct analyses which are difficult to assess with substantially smaller datasets.

1.2.2 Variables Construction

In this study, I set the unit of a workplace to be an office. It is defined and uniquely determined as a duty station (location) for a given government agency. For example, the Social Security Administration office in Boston, MA and the Social Security Administration office in Clemson, SC are considered two different offices. Examples of offices are shown in Exhibit 1.1 below.

The main variable of interest is $\log \text{Pay}_{i,t}$, the natural log real wage of an employee inflation adjusted to September 2011 dollars. I multiply the $\log \text{Pay}_{i,t}$ by 100 to enable a convenient coefficient interpretation as percentage changes.

The main independent variable of interest is the female leadership, it is aimed to measure the individual-specific female leadership in the office that excludes double-counting. Specifically, I construct variable $\text{FSup}_{i,j,t-1}$, the individual-specific current office's fraction of supervisors who are female in the previous period, excluding the impact of him/herself if counted. This construction is to account for the fact that a person's employment conditions like wage and promotion of a given year t are determined in the previous year $t-1$. The relevant circumstances that affect the employment contract should be based on the current office's previous year status. For example, if an individual i is now at office j, i's wage is determined by office j's status at year $t-1$. If i is counted in the fraction of female supervisors, then i will be subtracted from this calculation. Furthermore, I construct the variable $\text{FExec}_{i,j,t-1}$. Similar to the construction of the $\text{FSup}_{i,j,t-1}$, it computes the individual-specific fraction of executives who are female, excluding the impact of the individual. An individual is considered an executive if his/her basic pay is the highest among supervisors.

Aside from measuring period-by-period female leadership associated with each individual, I also compute a measure of female leadership exposure, a historical average over time of female leadership experienced by a particular individual, excluding double-counting. $\text{FSupHist}_{i,j,t-1}$ is the individual-specific historical average of corresponding female supervisors up to time $t-1$. This measures a person's past female supervisors that he/she has experienced. $\text{FExecHist}_{i,j,t-1}$ is similar to the construction of the $\text{FSupHist}_{i,j,t-1}$, the historical average of corresponding female executive leadership up to time $t-1$.

To facilitate econometric analysis robust to potential endogeneity, I construct an instrumental variables, using retirement as exogenous instrument[5]. Among the retiring leaders, I compute the relative fraction of male versus females. Since their leadership will disappear from the sample in the following year due to retirement, this fraction will not be subject to potential endogeneity concerns that may affect the next period outcome. The instrument is $\text{FSupIV}_{j,t-1}$, the fraction of male minus female among supervisors who are retiring in an office. For offices with no retiring supervisors, the value of the instrument is filled with population-wide average of 0.33. Corresponding to the female executive leadership, the instrument is $\text{FExecIV}_{j,t-1}$ which is a fraction of male minus female among executives who are retiring in an office. For offices with no retiring executives, the value of the instrument is filled with population-wide average of 0.64.

Next, I construct individual characteristics relating to human capital to serve as control variables. Variable $\text{Age}_{i,t}$ is the approximate age. Since the OPM dataset censors the potentially identifying information, including the actual age, the approximate age will be the actual age plus a random noise. Variable $\text{Tenure}_{i,t}$ is the number of years a person has been working in the federal government.

Further, I construct a list of variables reflecting a person's career mobility. Promotion, $\text{Prom}_{i,t}$, is an indicator variable that is 1 if a person i is promoted in year t. Since in the government sector, the occurrences of promotion follow specific rules, I further compute a measure of

[5]To construct the instrument, I follow the eligibility requirement in the OPM website, `https://www.opm.gov/retirement-services/fers-information/eligibility/`. I first compute the minimum retirement age (MRA) based on the Age variable, and then I combine it with tenure requirement to calculate whether a person is eligible to retire in the coming year. Further, I restrict the actual retirement to the condition that a person is eligible to retire and is leaving the dataset in the following year.

promotion that marks an employee becoming a supervisor, $\text{PromSup}_{i,t}$. It is an indicator variable that is 1 if a person i has ever been promoted from a non-supervisory status into a supervisory position in the past. To study an employee's propensity to exit the government sector, I also compute variable $\text{Exit}_{i,t}$, the indicator variable that is 1 if a person i left the government sector in year t not due to retirement. Since about 70% of employees are on the General Pay schedule, their pay is determined according to the pay grade and pay step. For these employees on the General Schedule pay, I construct the variable $\text{GradeStep}_{i,t}$, the grade-step of a person i ranging from 10 to 159 similar to Bolton and de Figueiredo (2017), where each change in the last digit represents a step rate change while a change in the second digit represents a pay grade change. To record an employee's starting and exiting pay status, I construct the variables $\text{GradeStepStart}_{i,t}$, the pay grade step of a person i when initially appeared in the data and variable $\text{GradeStepExit}_{i,t}$, the pay grade step of a person i when last appeared in the data.

1.2.3 Summary Statistics

Table 1.1 reports the summary statistics of the primary variable of interest, basic pay (wage) in 2011 dollars, by different categories, including gender, education, race, occupation, and office size. From the result, it is evident that the unconditional gender wage gap is significant, at about $17,000 per year in 2011 terms. Across the education categories, one can see that government employees with a professional degree receive the most compensation, followed by a Ph.D. and an Advanced Degree, with the lowest being a High School
degree, earning less than a half of what the professional degree employees earn. The pay by race also confirms the literature that Asian and White are among the top racial groups in earnings, while Black and American Indian are among the bottom racial groups in earnings. In terms of the occupation category, the table also replicates the results reported in Bolton and de Figueiredo (2017) that administrative and professional categories are among the highest earning occupation categories in the government sector. Finally, in terms of the office size breakdown, no significant differences are reported.[6]

Table 1.2 reports the major variables that will be used in the analysis, including their mean, standard deviation, minimum, median, and maximum.

[6] In the empirical study, I drop the observations when, on average, an office had less than 3 people over the period it appeared in the data. These tiny offices are problematic as there is no reliable way to precisely identify the effects from the small number of people. Figure A.1 and A.2 reports the relative frequency of offices less than 5 people, and above 5 people.

Table 1.1: **Summary Statistics of Basic Pay, by Categories**

Category	Avg. Basic Pay	Std. Dev. Basic Pay	# Obs.
Sex_i			
Male	$74,839	$35,025	717,306
Female	$57,750	$26,989	813,747
Educ_i			
H.S.	$49,078	$21,858	334,305
<Bachelor	$53,372	$23,585	490,278
Bachelor	$72,467	$26,772	328,289
Master	$84,189	$28,557	226,067
Professional	$118,344	$41,826	68,851
Advanced	$98,148	$31,353	2,338
PhD	$101,805	$30,343	58,072
Race_i			
Amer. Indian	$50,534	$24,518	38,597
Asian	$76,971	$35,138	61,848
Black	$52,979	$24,242	333,355
Hispanic	$58,890	$29,791	76,189
Other	$56,047	$37,241	63,635
White	$71,286	$32,683	957,429
Occu_i			
Admin.	$79,559	$27,050	476,767
Blue Coll.	$45,240	$15,590	110,350
Clerical	$33,670	$7,161	171,603
Other	$32,838	$9,755	7812
Professional	$86,746	$32,051	440,968
Technical	$41,607	$11,166	323,461
Office Size			
Tiny [0,25%]	$65,718	$29,589	382,765
Small (25%,50%]	$66,137	$32,242	383,530
Large (50%,75%]	$62,046	$33,019	379,925
Huge (75%,100%]	$69,077	$33,291	384,833

10% data, Offices with less than 3 employees are dropped.

Figure 1.2 reports the representation of female among executives/supervisors over time. We observe a significant increase in female executives/supervisors representation over time. However, the female representation is significantly lower among the executives than among the supervisors.

Figure 1.3 reports the female representation among different occupation categories over time. An immediate result from this figure shows that occupation categories are highly "gendered", i.e. there exist strong differentials in gender diversity across different categories. For example, blue collar is considered a mostly male category, while clerical is considered mostly a female category.

Table 1.2: **Summary Statistics of Major Variables**

Variable	Mean	Std. Dev.	Min	Median	Max
Year	1999	7.06	1988	1999	2011
Real Basic Pay	$64,628	$31,187	$0	$57,936	$1,548,281
Age	44.8	10.7	15	45	77
MidAge	44.7	10.9	17	47	77
Male	0.48	0.49	0	0	1
log(Pay)	1096.8	46.45	272.04	1096.71	1425.26
Ten	14.6	10.1	0	14	65
TenSq	317	354	0	196	4225
FSup	0.3754	0.2095	0	0.3939	1
FExec	0.2100	0.3790	0	0	1
FSupHist	0.3535	0.2004	0	0.375	1
FExecHist	0.1876	0.2612	0	0.0625	1
FSupIV	0.3282	0.4958	-1	0.3283	1
FExecIV	0.6398	0.2532	-1	0.6398	1
Step	4.37	2.98	0	4	9
GradeStep	98.37	33.83	10	103	159
Grade	9.39	3.34	1	10	18
Prom	17.53	38.02	0	0	100
PromSup	20.9	40.6	0	0	100
GradeStepStart	84.3	35.2	10	79	159
GradeStepExit	106	33	10	116	159
Exit	6.8	25	0	0	100

100% data, Offices with less than 3 employees are dropped.

Such trend can be seen directly from the figure.

Over the years, the real wage in the government sector has experienced a significant increase, both in terms of basic pay or adjusted pay as in Figure 1.4. It is also shown that in the year of 2008 there is a drop in all government workers' pay.

Figure 1.5 shows that as age increases, the median real wage increases for male workers but decreases when female workers are around 52 years old, after which female compensation is lower for female workers with higher age. Similarly for tenure, in Figure 1.6 as tenure increases, the median real wage increases for male workers but decreases when female workers reach 39 years tenure, after which female compensation is lower for female workers with higher tenure.

1.3 Female Leadership and Wage

I first establish the main result that female leadership increases female workers wage, decreases male workers pay, and reduces the gender gap in the government sector. I design the following benchmark model with the office fixed effects and the individual fixed effects based on the Mincer equation.

1.3.1 Benchmark

To establish the benchmark model and examine the overall gender wage gap, I use the following office level fixed effect panel regression specification to explain the wage of a government employee:

$$\begin{aligned}\log \text{Pay}_{i,t} &= \alpha + \beta_1 \text{FLead}_{i,j,t-1} + \beta_2 \text{FLead}_{i,j,t-1}\text{Male}_i + \beta_3 \text{Male}_i \\ &+ \gamma_1 \text{Age}_{i,t-1} + \gamma_2 \text{Tenure}_{i,t-1} + \gamma_3 \text{Tenure}^2_{i,t-1} \\ &+ \sum_{e\in(\text{EducGrp})} \theta_e d^e_{i,t-1} + \sum_{r\in(\text{Race})} \theta_r d^r_i + \sum_{m\in(\text{AgeGrp})} \theta_m d^m_{i,t-1} \\ &+ \sum_{o\in(\text{OccGrp})} \theta_o d^o_{i,t-1} + \sum_{y\in(\text{Year})} \theta_y d^y_{i,t} + \sum_{j\in(\text{Office})} \theta_j d^j_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{1.1}$$

where the coefficient β_1 indicates the effect of female leadership on female employees' wages. Standard errors are clustered at the office level.

To better control for the unobserved individual heterogeneity that could potentially impact the coefficients of interest, I also estimate the following individual fixed effect panel regression specification to explain the wage of a government employee:

$$\begin{aligned}\log \text{Pay}_{i,t} &= \alpha + \beta_1 \text{FLead}_{i,j,t-1} + \beta_2 \text{FLead}_{i,j,t-1}\text{Male}_i + \gamma_2 \text{Tenure}_{i,t-1} + \gamma_3 \text{Tenure}^2_{i,t-1} \\ &+ \sum_{e\in(\text{EducGrp})} \theta_e d^e_{i,t-1} + \sum_{m\in(\text{AgeGrp})} \theta_m d^m_{i,t-1} + \sum_{y\in(\text{Year})} \theta_y d^y_{i,t} + \sum_i \theta_i d_i + \epsilon_{i,t}, \end{aligned} \tag{1.2}$$

where the coefficient β_1 indicate the effect of female leadership on female employee wages.

Table 3.3 reports the results when I use $\text{FSup}_{i,j,t-1}$ as the measure for $\text{FLead}_{i,j,t-1}$. It shows that female leadership significantly increases female wages, decreases male wages, and reduces the overall gender gap. Specifically, when the female supervisors are all female compared with all male,

Table 1.3: **Female Supervisors & log(Basic Pay), All Service Status, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t-1}$	7.053*** (0.417)	2.513*** (0.0590)	3.864*** (0.178)	8.050*** (1.092)	11.83*** (2.250)	15.13** (6.615)
$(\beta_2)\text{FSup}_{i,j,t-1} \times \text{Male}_i$	-13.83*** (0.626)	-1.963*** (0.0889)	-7.072*** (0.254)	-17.47*** (1.043)	-19.50*** (2.636)	-21.12*** (3.364)
$(\beta_3)\text{Male}_i$	10.63*** (0.305)	— —	9.717*** (0.132)	12.62*** (0.443)	12.38*** (1.160)	13.93*** (1.591)
$(\gamma_1)\text{Age}_{i,t-1}$	0.268*** (0.0117)	— —	0.219*** (0.00687)	0.225*** (0.0129)	0.282*** (0.0188)	0.285*** (0.0369)
$(\gamma_2)\text{Tenure}_{i,t-1}$	1.686*** (0.0238)	1.412*** (0.00810)	2.000*** (0.0154)	1.788*** (0.0311)	1.472*** (0.0316)	1.673*** (0.0746)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	-0.0203*** (0.000585)	-0.0317*** (0.0000941)	-0.0245*** (0.000360)	-0.0215*** (0.000703)	-0.0174*** (0.000700)	-0.0212*** (0.00190)
$p(\beta_1 + \beta_2 = 0)$	0.0000	0.0000	0.0000	0.0000	0.0021	0.3790
$p(\beta_2 + \beta_3 = 0)$	0.0000	—	0.0000	0.0000	0.0000	0.0004
R^2_{Adj}	0.720	0.709	0.712	0.711	0.751	0.730
#Obs	15,746,338	15,746,338	3,848,257	3,949,523	3,938,562	4,009,996
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

the female wages increase by 7% while male wages decrease by 6.8%, the gender wage gap drops from 10.63% in favor of men to -3.2% in favor of women. These results are all highly statistically significant. Similar significant effect, but in a smaller magnitude, is also observed at the individual level, where female leadership increases female workers wages.

Next, I use $\text{FExec}_{i,j,t-1}$ as the measure for $\text{FLead}_{i,j,t-1}$, and report the results in Table 3.4. Compared to the effect of the female supervisors, the female executive's impact on worker's wage is smaller in magnitude and is most significant at small office sizes. For example, overall, when an office is lead by a female executive rather than a male executive, female workers' wages will increase on average by 0.67%. The executive's effect is the strongest at the smallest, Size (1), and smaller, Size (2), offices which amounts to 1.96% and 0.63% respectively. This effect is statistically insignificant at larger, Size (3) and the largest, Size (4) offices.

Table 1.4: **Female Executives & log(Basic Pay), All Service Status, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
(β_1)FExec$_{i,j,t-1}$	0.667*** (0.154)	0.331*** (0.0144)	1.955*** (0.114)	0.631*** (0.206)	0.450 (0.285)	0.324 (0.397)
(β_2)FExec$_{i,j,t-1}$ $\times$ Male$_i$	-1.979*** (0.225)	-0.271*** (0.0221)	-4.207*** (0.154)	-1.799*** (0.339)	-0.957** (0.454)	-1.046* (0.565)
(β_3)Male$_i$	5.712*** (0.226)	— —	8.413*** (0.111)	6.532*** (0.240)	4.187*** (0.328)	5.140*** (0.672)
(γ_1)Age$_{i,t-1}$	0.269*** (0.0116)	— —	0.219*** (0.00684)	0.225*** (0.0129)	0.283*** (0.0189)	0.289*** (0.0366)
(γ_2)Tenure$_{i,t-1}$	1.690*** (0.0239)	1.415*** (0.00806)	2.005*** (0.0153)	1.792*** (0.0311)	1.470*** (0.0319)	1.668*** (0.0763)
(γ_3)Tenure$^2_{i,t-1}$	-0.0204*** (0.000587)	-0.0318*** (0.0000942)	-0.0251*** (0.000358)	-0.0216*** (0.000701)	-0.0173*** (0.000708)	-0.0210*** (0.00194)
$p(\beta_1+\beta_2=0)$	0.0000	0.0003	0.0000	0.0000	0.148	0.120
$p(\beta_2+\beta_3=0)$	0.0000	—	0.0000	0.0000	0.0000	0.0000
R^2_{Adj}	0.719	0.709	0.711	0.710	0.750	0.729
#Obs	15,691,416	15,691,416	3,803,200	3,942,227	3,936,604	4,009,385
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1.3.2 Instrumental Variables Approach

To guard against the potential endogeneity, I further employ an instrumental variable approach to study the effect of female leadership on employees' wages. The instrument I chose is based on the retirement. I assume that retirement affects next period employees' wages only through changing gender decomposition in the leadership positions. The construction of the instrument is detailed in the previous section.

Using the fraction of male among retiring leaders minus the fraction of female among retiring leaders as an instrumental variable, I study the effect of female leadership using Two Stage Least Square (2SLS) approach. The first stage involves predicting female leadership using the instrumental variables. Then, I estimate the following equations (1.3) and (1.4) to obtain the predicted

Table 1.5: **Instrumented Female Supervisors, First Stage, 100% Data**

	(1)	(2)
	$\text{FSup}_{i,j,t-1}$	$\text{FSup}_{i,j,t-1} \times \text{Male}_i$
$(\delta_1)\text{FSupIV}_{i,j,t-1}$	-0.0221***	0.0553***
	(0.000920)	(0.00266)
$(\delta_2)\text{FSupIV}_{i,j,t-1} \times \text{Male}_i$	-0.00117***	-0.148***
	(0.000398)	(0.00629)
$(\delta_3)\text{Male}_i$	-0.000722***	0.430***
	(0.000169)	(0.00462)
$(\delta_4)\text{Age}_{i,t-1}$	-0.0000176	-0.0000417**
	(0.0000155)	(0.0000189)
$(\delta_5)\text{Tenure}_{i,t-1}$	-0.000333***	-0.000299***
	(0.0000539)	(0.0000517)
$(\delta_6)\text{Tenure}^2_{i,t-1}$	0.00000660***	-0.00000379***
	(0.00000129)	(0.00000138)
R^2_{Adj}	0.153	0.787
#Obs	15,750,921	15,750,921
F-stat	56.63	834.4
Joint p	0.0000	0.0000
Office FE	✓	✓
Race, OccGrp FE	✓	✓
Educ, Age, Year FE	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

explanatory variables that are potentially endogenous:

$$\begin{aligned}\text{FLead}_{i,j,t-1} = {} & \delta_0 + \delta_1 \text{IV}_{i,j,t-1} + \delta_2 \text{IV}_{i,j,t-1}\text{Male}_i + \delta_3 \text{Male}_i \\ & + \delta_4 \text{Age}_{i,t} + \delta_5 \text{Tenure}_{i,t-1} + \delta_6 \text{Tenure}^2_{i,t-1} \\ & + \sum_{e \in (\text{EducGrp})} \delta_e d^e_{i,t-1} + \sum_{r \in (\text{Race})} \delta_r d^r_i + \sum_{m \in (\text{AgeGrp})} \delta_m d^m_{i,t-1} \\ & + \sum_{o \in (\text{OccGrp})} \delta_o d^o_{i,t-1} + \sum_{y \in (\text{Year})} \delta_y d^y_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{1.3}$$

Table 1.6: **Instrumented Female Supervisors & log(Basic Pay), Second Stage, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\widehat{\text{FSup}}_{i,j,t-1}$	11.33***	7.696***	5.145***	7.657***	5.503***	15.23***
	(0.541)	(0.226)	(0.529)	(1.150)	(1.347)	(1.789)
$(\beta_2)\widehat{\text{FSup}_{i,j,t-1} \times \text{Male}_i}$	-18.55***	-6.607***	-6.433***	-17.84***	-20.12***	-20.02***
	(0.140)	(0.290)	(0.377)	(0.294)	(0.354)	(0.2 10)
$(\beta_3)\text{Male}_i$	12.44***	—	9.532***	12.76***	12.64***	13.47***
	(0.0548)	—	(0.114)	(0.110)	(0.154)	(0.0929)
$(\gamma_1)\text{Age}_{i,t-1}$	0.267***	—	0.219***	0.225***	0.282***	0.285***
	(0.00220)	—	(0.00392)	(0.00437)	(0.00446)	(0.00452)
$(\gamma_2)\text{Tenure}_{i,t-1}$	1.686***	1.414***	2.001***	1.788***	1.471***	1.673***
	(0.00203)	(0.00274)	(0.00380)	(0.00409)	(0.00400)	(0.00411)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	-0.0204***	-0.0317***	-0.0245***	-0.0215***	-0.0174***	-0.0212***
	(0.0000553)	(0.0000335)	(0.000102)	(0.000111)	(0.000112)	(0.000111)
$p(\beta_1 + \beta_2 = 0)$	0.0000	0.0000	0.0251	0.0000	0.0000	0.0065
$p(\beta_2 + \beta_3 = 0)$	0.0000	—	0.0000	0.0000	0.0000	0.0000
#Obs	15,746,338	15,746,338	3,848,257	3,949,523	3,938,562	4,009,996
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

and

$$\begin{aligned}
\text{FLead}_{i,j,t-1}\text{Male}_i = {} & \delta'_0 + \delta'_1\text{IV}_{i,j,t-1} + \delta'_2\text{IV}_{i,j,t-1}\text{Male}_i + \delta'_3\text{Male}_i \\
& + \delta'_4\text{Age}_{i,t} + \delta'_5\text{Tenure}_{i,t-1} + \delta'_6\text{Tenure}^2_{i,t-1} \\
& + \sum_{e\in(\text{EducGrp})} \delta'_e d^e_{i,t-1} + \sum_{r\in(\text{Race})} \delta'_r d^r_i + \sum_{m\in(\text{AgeGrp})} \delta'_m d^m_{i,t-1} \\
& + \sum_{o\in(\text{OccGrp})} \delta'_o d^o_{i,t-1} + \sum_{y\in(\text{Year})} \delta'_y d^y_{i,t} + \varepsilon'_{i,t}. \qquad (1.4)
\end{aligned}$$

The second stage regresses the response variables of interest on the predicted female leadership variables as follows:

$$
\begin{aligned}
\log \text{Pay}_{i,t} &= \alpha + \beta_1 \widehat{\text{FLead}}_{i,j,t-1} + \beta_2 \text{FLead}\widehat{_{i,j,t-1}}\text{Male}_i + \beta_3 \text{Male}_i \\
&+ \gamma_1 \text{Age}_{i,t-1} + \gamma_2 \text{Tenure}_{i,t-1} + \gamma_3 \text{Tenure}^2_{i,t-1} \\
&+ \sum_{e \in (\text{EducGrp})} \theta_e d^e_{i,t-1} + \sum_{r \in (\text{Race})} \theta_r d^r_i + \sum_{m \in (\text{AgeGrp})} \theta_m d^m_{i,t-1} \\
&+ \sum_{o \in (\text{OccGrp})} \theta_o d^o_{i,t-1} + \sum_{y \in (\text{Year})} \theta_y d^y_{i,t} + \sum_{j \in (\text{Office})} \theta_j d^j_{i,t} + \epsilon_{i,t}.
\end{aligned}
\tag{1.5}
$$

Table 3.5 reports the first stage regression where predicted values of $\text{FSup}_{i,j,t-1}$ and $\text{FSup}_{i,j,t-1}\text{Male}_i$ are computed. The retirement instrument is highly relevant since the F-statistics well exceeds a typical threshold of ten for the joint model significance.

Next, I report the second stage estimation results in Table 3.6. Compared with the benchmark case, the coefficients qualitatively do not change; however, the effect of female leadership is stronger. Overall, purely female supervisory leadership increases female wages by 11.3% and reduces male worker's wages by 6.2% comparing to purely male leadership. The gender gap under all female supervisors is statistically significant and is - 6.1% , a reverse gender gap is observed. It means women are earning more than men under purely female leadership. This results based on the instrumental variable approach are significant and further corroborate with the previous results using individual-specific female leadership.

1.4 Female Leadership and Career Mobility

After observing the statistically and economically significant effect of female leadership on employees' wages in the previous sections, I further investigate through what channels these results take place. By analyzing a propensity to promote or to exit, and starting or exiting positions, I find that under female leadership, female employees have higher propensity to be promoted, a higher starting position and a higher exiting position than under male leadership. For male employees, female leadership decreases their chances to be promoted and increases their chances to exit an office and have lower exiting positions.

1.4.1 Female Leadership and Promotion

I use the following office level fixed effect panel regression specification to investigate whether the female leadership affects employee propensity to promote:

$$
\begin{aligned}
\{\text{PromSup}_{i,t}, \text{Prom}_{i,t}\} = \alpha &+ \beta_1 \text{FLead}_{i,j,t-1} + \beta_2 \text{FLead}_{i,j,t-1}\text{Male}_i + \beta_3 \text{Male}_i \\
&+ \gamma_1 \text{Age}_{i,t-1} + \gamma_2 \text{Tenure}_{i,t-1} + \gamma_3 \text{Tenure}^2_{i,t-1} \\
&+ \sum_{e \in (\text{EducGrp})} \theta_e d^e_{i,t-1} + \sum_{r \in (\text{Race})} \theta_r d^r_i + \sum_{m \in (\text{AgeGrp})} \theta_m d^m_{i,t-1} \\
&+ \sum_{o \in (\text{OccGrp})} \theta_o d^o_{i,t-1} + \sum_{y \in (\text{Year})} \theta_y d^y_{i,t} + \sum_{j \in (\text{Office})} \theta_j d^j_{i,t} + \epsilon_{i,t}. \qquad (1.6)
\end{aligned}
$$

Similarly, I also estimate the individual fixed effect panel regression specification to better control for the unobserved individual heterogeneity that could potentially impact the coefficients of interest in the following equation:

$$
\begin{aligned}
\{\text{PromSup}_{i,t}, \text{Prom}_{i,t}\} = \alpha &+ \beta_1 \text{FLead}_{i,j,t-1} + \beta_2 \text{FLead}_{i,j,t-1}\text{Male}_i \\
&+ \gamma_2 \text{Tenure}_{i,t-1} + \gamma_3 \text{Tenure}^2_{i,t-1} \\
&+ \sum_{e \in (\text{EducGrp})} \theta_e d^e_{i,t-1} + \sum_{m \in (\text{AgeGrp})} \theta_m d^m_{i,t-1} \\
&+ \sum_{y \in (\text{Year})} \theta_y d^y_{i,t} + \sum_i \theta_i d_i + \epsilon_{i,t}. \qquad (1.7)
\end{aligned}
$$

Table 1.7 reports the effect of female supervisor leadership on the propensity to ever be promoted into a supervisory status from a non-supervisory position. Under female leadership, female workers have a 4.8% higher chance on average to ever be promoted into a supervisory position from a non-supervisory position. At the same time, male workers have are 1% less likely to ever be promoted into a supervisory position, the p-value of this estimate is 0.01%. Moreover, under female leadership, the gender promotion gap decreases statistically significantly from 4% to -1.6% compared to under male leadership.

Similar results are obtained if the explanatory variable is replaced by the propensity to be promoted to the next grade. Table 3.9 shows that under female leadership, female employees are 1% chance more likely to be promoted based on pay grade, and for male employees, about 1% less likely than under male leadership. The promotion gap almost disappears once the office switches

Table 1.7: **Female Supervisors & Propensity to Promote Into Supervisory Status, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t-1}$	4.854*** (0.337)	1.513*** (0.143)	3.746*** (0.243)	6.108*** (0.950)	9.567*** (2.256)	29.89*** (5.588)
$(\beta_2)\text{FSup}_{i,j,t-1} \times \text{Male}_i$	-5.808*** (0.426)	2.729*** (0.231)	-7.156*** (0.341)	-3.436*** (0.871)	-4.371** (1.930)	-6.291*** (2.049)
$(\beta_3)\text{Male}_i$	4.196*** (0.203)	— —	4.570*** (0.172)	3.149*** (0.398)	3.130*** (0.937)	4.662*** (0.978)
$(\gamma_1)\text{Age}_{i,t-1}$	-0.138*** (0.00526)	— —	-0.172*** (0.00888)	-0.129*** (0.0101)	-0.117*** (0.0105)	-0.138*** (0.0125)
$(\gamma_2)\text{Tenure}_{i,t-1}$	1.340*** (0.0278)	0.450*** (0.0127)	1.463*** (0.0205)	1.411*** (0.0313)	1.142*** (0.0412)	1.376*** (0.0841)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	-0.0203*** (0.000700)	-0.00677*** (0.000217)	-0.0208*** (0.000591)	-0.0203*** (0.000848)	-0.0178*** (0.00111)	-0.0225*** (0.00196)
$p(\beta_1 + \beta_2 = 0)$	0.0111	0	0	0.00846	0.0147	0.0000
$p(\beta_2 + \beta_3 = 0)$	0	—	0	0.594	0.229	0.158
R^2_{Adj}	0.0958	0.133	0.107	0.100	0.0929	0.0888
#Obs	14,066,540	14,066,540	3,389,924	3,487,597	3,564,246	3,624,773
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

from male leadership to female leadership. It is worth noting that the promotion is more significant at the smaller offices, which supports the conjecture that there may exist a radius of the effect of female leadership. This effect is stronger in smaller offices where employees are closer to the female leaders. I further detail on this in later sections.

1.4.2 Female Leadership and Exiting

Aside from studying the effect of female leadership on promotion, I also investigate how female leadership affects employees' propensity to exit an office. I find that for female workers, female leadership has no significant effect on their propensity to exit; however, for male workers, female leadership increases the propensity to exit by 0.4%, a statistically significant increase compared to under male leadership. This helps to explain why female leadership significantly decreases male workers' wages by increasing their propensity to exit.

I estimate the following regression specification controlling for grade and step fixed effect

Table 1.8: **Female Supervisors & Propensity to Promote on Pay Grade, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t-1}$	0.976*** (0.326)	2.309*** (0.158)	1.179*** (0.216)	2.596** (1.208)	-2.495 (2.497)	1.758 (6.361)
$(\beta_2)\text{FSup}_{i,j,t-1} \times \text{Male}_i$	-1.915*** (0.279)	-1.894*** (0.228)	-2.766*** (0.208)	-1.868*** (0.579)	1.548 (1.158)	-4.163*** (1.352)
$(\beta_3)\text{Male}_i$	1.434*** (0.137)	— —	3.013*** (0.101)	1.242*** (0.249)	-0.347 (0.556)	2.115*** (0.753)
$(\gamma_1)\text{Age}_{i,t-1}$	-0.333*** (0.00736)	— —	-0.277*** (0.00934)	-0.354*** (0.0107)	-0.329*** (0.0146)	-0.367*** (0.0202)
$(\gamma_2)\text{Tenure}_{i,t-1}$	-0.929*** (0.0353)	0.0170 (0.0188)	-0.939*** (0.0166)	-1.047*** (0.0325)	-0.731*** (0.0460)	-0.960*** (0.102)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	0.0204*** (0.000845)	-0.00720*** (0.000218)	0.0228*** (0.000388)	0.0228*** (0.000752)	0.0151*** (0.00105)	0.0193*** (0.00242)
$p(\beta_1 + \beta_2 = 0)$	0.00360	0.0145	0.0000	0.555	0.726	0.689
$p(\beta_2 + \beta_3 = 0)$	0.0103	—	0.104	0.0848	0.0554	0.00285
R^2_{Adj}	0.172	0.222	0.190	0.187	0.152	0.172
#Obs	11,279,131	112,79,131	2,986,201	2,854,929	2,592,393	2,845,608
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓
Step FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

and report the result in Table 1.9:

$$\begin{aligned}
\text{Exit}_{i,t} &= \alpha + \beta_1 \text{FLead}_{i,j,t} + \beta_2 \text{FLead}_{i,j,t}\text{Male}_i + \beta_3 \text{Male}_i \\
&+ \gamma_1 \text{Age}_{i,t} + \gamma_2 \text{Tenure}_{i,t} + \gamma_3 \text{Tenure}^2_{i,t} \\
&+ \sum_{e \in (\text{EducGrp})} \theta_e d^e_{i,t} + \sum_{r \in (\text{Race})} \theta_r d^r_i + \sum_{m \in (\text{AgeGrp})} \theta_m d^m_{i,t} \\
&+ \sum_{o \in (\text{OccGrp})} \theta_o d^o_{i,t} + \sum_{y \in (\text{Year})} \theta_y d^y_{i,t} + \sum_{j \in (\text{Office})} \theta_j d^j_{i,t} + \epsilon_{i,t}. \qquad (1.8)
\end{aligned}$$

1.4.3 Female Leadership and Starting Position

Female leadership also impacts the starting position of a new employee. Under female leadership, female employees start one step higher than under male employee; while for a male employee, female leadership causes a 2.7 step decline in starting grade-step. The gender gap in

Table 1.9: **Female Supervisors & Propensity to Exit, 100% Data**

	(1)	Office Size Quartile			
	Office FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t-1}$	0.949 (0.757)	0.131 (0.101)	0.500 (0.483)	-0.0347 (0.844)	25.22 (20.64)
$(\beta_2)\text{FSup}_{i,j,t-1} \times \text{Male}_i$	0.432*** (0.152)	0.501*** (0.109)	0.614*** (0.220)	1.211*** (0.415)	-0.358 (0.615)
$(\beta_3)\text{Male}_i$	0.0574 (0.0632)	0.0821* (0.0466)	0.150* (0.0883)	-0.267 (0.189)	0.253 (0.301)
$(\gamma_1)\text{Age}_{i,t-1}$	0.181*** (0.00635)	0.220*** (0.00555)	0.194*** (0.00708)	0.188*** (0.00907)	0.137*** (0.0171)
$(\gamma_2)\text{Tenure}_{i,t-1}$	-0.688*** (0.0118)	-0.676*** (0.0101)	-0.696*** (0.0157)	-0.695*** (0.0186)	-0.653*** (0.0287)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	0.0229*** (0.000339)	0.0233*** (0.000288)	0.0231*** (0.000409)	0.0228*** (0.000562)	0.0216*** (0.000815)
$p(\beta_1 + \beta_2 = 0)$	0.0337	0.0000	0.0177	0.170	0.221
$p(\beta_2 + \beta_3 = 0)$	0.0000	0.0000	0.0000	0.0000	0.753
R^2_{Adj}	0.0552	0.0653	0.0553	0.0509	0.0554
#Obs	12,433,292	3,260,132	3,156,277	2,876,962	3,139,921
Office FE	✓	✓	✓	✓	✓
Race, OccGrp FE	✓	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓
Step FE	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

terms of starting grade-step is reduced from 5.6 steps under male leadership to 2.9 steps under female leadership while it still remains statistically significant from zero.

I estimate the following regression using starting grade-step as the dependent variable and report the results in Table 1.10:

$$\begin{aligned}
\text{GradeStepStart}_{i,t} &= \alpha + \beta_1 \text{FLead}_{i,j,t-1} + \beta_2 \text{FLead}_{i,j,t-1}\text{Male}_i + \beta_3 \text{Male}_i \\
&\quad + \gamma_1 \text{Age}_{i,t-1} + \gamma_2 \text{Tenure}_{i,t-1} + \gamma_3 \text{Tenure}^2_{i,t-1} \\
&\quad + \sum_{e \in (\text{EducGrp})} \theta_e d^e_{i,t-1} + \sum_{r \in (\text{Race})} \theta_r d^r_i + \sum_{m \in (\text{AgeGrp})} \theta_m d^m_{i,t-1} \\
&\quad + \sum_{o \in (\text{OccGrp})} \theta_o d^o_{i,t-1} + \sum_{y \in (\text{Year})} \theta_y d^y_{i,t} + \sum_{j \in (\text{Office})} \theta_j d^j_{i,t-1} + \epsilon_{i,t}. \qquad (1.9)
\end{aligned}$$

Table 1.10: **Female Supervisors & Starting Grade-Step, All Service Status, 10% Data**

	(1)	Office Size Quartile			
	10% Sample	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t-1}$	1.050 (0.639)	0.441 (0.748)	0.162 (1.561)	3.572* (2.131)	11.47*** (3.721)
$(\beta_2)\text{FSup}_{i,j,t-1} \times \text{Male}_i$	-2.724*** (0.688)	-1.306 (0.812)	-4.472*** (1.582)	-5.021* (2.795)	-6.082 (3.737)
$(\beta_3)\text{Male}_i$	5.646*** (0.353)	6.479*** (0.438)	5.954*** (0.879)	5.016*** (1.252)	6.185*** (1.880)
$(\gamma_1)\text{Age}_{i,t-1}$	0.224*** (0.0349)	0.156*** (0.0556)	0.262*** (0.0665)	0.159** (0.0766)	0.369*** (0.0786)
$(\gamma_2)\text{Tenure}_{i,t-1}$	0.732*** (0.0417)	0.781*** (0.0607)	0.679*** (0.0811)	0.813*** (0.0922)	0.641*** (0.133)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	-0.00280** (0.00122)	-0.00325* (0.00174)	-0.00282 (0.00241)	-0.00512* (0.00295)	-0.00102 (0.00407)
$p(\beta_1 + \beta_2 = 0)$	0.0123	0.255	0.0134	0.594	0.223
$p(\beta_2 + \beta_3 = 0)$	0.0000	0.0000	0.155	0.998	0.959
R^2_{Adj}	0.627	0.591	0.643	0.666	0.655
#Obs	51,915	24,319	11,500	8,755	7,341
Office FE	✓	✓	✓	✓	✓
Race, OccGrp FE	✓	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓

10% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1.4.4 Female Leadership and Exiting Position

Similar to a starting position, I also estimate the impact of female leadership on an exiting position. This aims to uncover whether female leadership helps to retain female employees and therefore contributes to the outcome of the increasing female wages. The findings are exactly the case. Female leadership increases female workers' exiting pay grade-step by 2.5 steps. Given that in the government sector, promotion happens at a close to a deterministic pace, a higher exiting pay grade-step contributes to the observed increase in female workers' wage under female leadership. At the same time, female leadership significantly lowers the male exiting grade step by three steps. Combined with the previous findings that male workers start at a higher position, have higher chances to exit and have a lower exiting grade-step, this indicates that female leadership increases the turnover of male employees. This result is consistent with my findings that female leadership significantly decreases male wages.

Table 1.11: **Female Supervisors & Exiting Grade-Step, All Service Status, 10% Data**

	(1)	Office Size Quartile			
	All Sizes	Size (1)	Size (2)	Size (3)	Size (4)
(β_1)FSup$_{i,j,t-1}$	2.480*** (0.445)	2.130*** (0.548)	2.769*** (0.873)	1.963* (1.183)	6.853** (3.228)
(β_2)FSup$_{i,j,t-1}$ $\times$ Male$_i$	-5.528*** (0.530)	-5.213*** (0.617)	-4.580*** (1.041)	-4.252** (1.681)	-7.665*** (2.719)
(β_3)Male$_i$	4.590*** (0.294)	5.614*** (0.342)	3.685*** (0.547)	3.389*** (0.918)	5.661*** (1.409)
(γ_1)Age$_{i,t-1}$	0.110*** (0.0264)	0.0748 (0.0493)	0.0570 (0.0469)	0.125*** (0.0428)	0.179*** (0.0631)
(γ_2)Tenure$_{i,t-1}$	0.945*** (0.0264)	1.118*** (0.0463)	0.877*** (0.0404)	0.787*** (0.0415)	1.008*** (0.0692)
(γ_3)Tenure$^2_{i,t-1}$	-0.0101*** (0.000616)	-0.0128*** (0.00106)	-0.00905*** (0.000974)	-0.00686*** (0.000942)	-0.0120*** (0.00158)
$p(\beta_1+\beta_2=0)$	0.0000	0.0000	0.0928	0.186	0.840
$p(\beta_2+\beta_3=0)$	0.00243	0.370	0.149	0.314	0.151
R^2_{Adj}	0.769	0.758	0.782	0.780	0.766
#Obs	83,260	21,997	20,399	20,087	20,777
Office FE	✓	✓	✓	✓	✓
Race, OccGrp FE	✓	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓

10% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

1.5 The Effective Radius of Female Leadership

In this section, I discuss the findings that female leadership seems to exhibit a limited radius of the effect on an employee's career outcome. I further provide a potential link of this pattern to the theoretical model of mentorship.

1.5.1 Female Leadership Has Limited Effective Radius

I first document the pattern of the radius of the effect of female leadership. I explore the two dimensions of the variation: the size of the office and the ranking of employees. I find that female leadership is mostly effective at influencing employees' wage and promotion outcomes when the office size is smaller, and when the ranking of the employee is closer to that of the female leader.

Table 1.12 reports the effect of the female executive leadership on workers who are of a supervisory status, across different office sizes. Table 1.13 reports the effect of the female executive leadership on workers who are of a non-supervisory status.

Several observations can be made: first, the female executive's impact is stronger at offices

Table 1.12: **Female Executives & log(Basic Pay), Supervisors, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FExec}_{i,j,t-1}$	1.300*** (0.264)	0.410*** (0.0361)	6.399*** (0.218)	1.184*** (0.263)	-0.0415 (0.364)	-0.765 (0.585)
$(\beta_2)\text{FExec}_{i,j,t-1} \times \text{Male}_i$	-3.076*** (0.226)	-0.653*** (0.0467)	-9.998*** (0.268)	-2.375*** (0.319)	-0.579 (0.423)	-0.0191 (0.434)
$(\beta_3)\text{Male}_i$	6.305*** (0.147)	— —	9.067*** (0.160)	5.840*** (0.197)	5.386*** (0.263)	5.203*** (0.413)
$(\gamma_1)\text{Age}_{i,t-1}$	0.410*** (0.0158)	— —	0.330*** (0.0135)	0.386*** (0.0197)	0.437*** (0.0257)	0.435*** (0.0469)
$(\gamma_2)\text{Tenure}_{i,t-1}$	0.664*** (0.0329)	0.892*** (0.0175)	0.990*** (0.0324)	0.671*** (0.0438)	0.622*** (0.0653)	0.536*** (0.0772)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	-0.00178*** (0.000564)	-0.0201*** (0.000245)	-0.00611*** (0.000687)	-0.00118 (0.000882)	-0.00212* (0.00128)	-0.000320 (0.00130)
$p(\beta_1 + \beta_2 = 0)$	0.0000	0.0000	0.0000	0.0000	0.0241	0.247
$p(\beta_2 + \beta_3 = 0)$	0.0000	—	0.0000	0.0000	0.0000	0.0000
R^2_{Adj}	0.542	0.688	0.472	0.507	0.600	0.604
#Obs	2,539,298	2,539,298	686,916	687,322	566,450	598,610
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

that are smaller in size, as indicated by the magnitude and the statistical significance change as one moves to larger offices. This pattern holds true for both samples of supervisors and non-supervisors. Second, comparing the effect of female executives on supervisors, who have a higher pay scale ranking than non-supervisors, the effect on supervisors is uniformly stronger than that on non-supervisors. Third, the effect of female executives on employees is generally weaker than that of the female supervisors. These three patterns not only hold true for the coefficient β_1, but also for β_2 and β_3.

When an office is smaller, or when the employee has a higher ranking, or when the leader is ranked closer to the employee, the distance between female leadership is naturally smaller compared to the situation when the office is larger, or when the employee has low service status rankings, or the leader is ranked high and is located far from the employee. These findings suggest that female leadership may have an aura with a limited radius that affects the employee career outcome.

This pattern of limited radius not only applies to wage regressions, but also applies when the propensity to promote is in question. Similar pattern is observed in Table 1.14 and Table 1.15.

Table 1.13: **Female Executives & log(Basic Pay), Non-Supervisors, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
(β_1)FExec$_{i,j,t-1}$	0.390*** (0.141)	0.291*** (0.0146)	0.592*** (0.107)	0.502** (0.209)	0.374 (0.292)	0.497 (0.360)
(β_2)FExec$_{i,j,t-1} \times$ Male$_i$	-1.321*** (0.222)	-0.136*** (0.0236)	-1.587*** (0.154)	-1.505*** (0.358)	-0.981** (0.452)	-1.058* (0.559)
(β_3)Male$_i$	4.312*** (0.239)	— —	6.344*** (0.116)	5.334*** (0.263)	3.075*** (0.335)	4.009*** (0.697)
(γ_1)Age$_{i,t-1}$	0.262*** (0.0105)	— —	0.215*** (0.00633)	0.213*** (0.0116)	0.273*** (0.0175)	0.282*** (0.0323)
(γ_2)Tenure$_{i,t-1}$	1.638*** (0.0228)	1.454*** (0.00848)	1.985*** (0.0145)	1.733*** (0.0308)	1.434*** (0.0317)	1.584*** (0.0701)
(γ_3)Tenure$^2_{i,t-1}$	-0.0229*** (0.000550)	-0.0341*** (0.000101)	-0.0289*** (0.000348)	-0.0244*** (0.000711)	-0.0196*** (0.000716)	-0.0223*** (0.00176)
$p(\beta_1+\beta_2=0)$	0.0000	0.0000	0.0000	0.0004	0.0968	0.228
$p(\beta_2+\beta_3=0)$	0.0000	—	0.0000	0.0000	0.0000	0.0000
R^2_{Adj}	0.726	0.704	0.719	0.718	0.755	0.734
#Obs	13,152,118	13,152,118	3,116,284	3,254,905	3,370,154	3,410,775
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In smaller offices the effect of female leadership is stronger and female supervisors have a stronger effect on workers career outcome than the female executive leadership.

1.5.2 A Potential Mentorship Story

In the related literature that studies the impact of female leadership on employee career outcome, there are three mutually exclusive theories that are currently being actively explored in empirical studies, namely (1) statistical-based discrimination, (2) taste-based discrimination, and (3) gender complementarity.

The statistical-based discrimination theory originates from the model of Phelps (1972). Taking the recent study of Flabbi, Macis, Moro, and Schivardi (2016) as an example, the basic framework is the following: there are two types of jobs (complex task and simple task) and two types of leaders (male and female). The leader assigns workers to jobs and wages based on a noisy signal of workers' ability. If the leaders are better at reading productivity signals of workers from the same gender, then compared with a male leader, who cannot accurately differentiate productive and un-

Table 1.14: **Female Executives & Propensity to Promote Into Supervisory Status, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
(β_1)FExec$_{i,j,t-1}$	0.402*** (0.108)	0.182*** (0.0330)	1.313*** (0.148)	-0.252 (0.181)	0.333* (0.175)	0.0897 (0.270)
(β_2)FExec$_{i,j,t-1}$ $\times$ Male$_i$	-0.393** (0.172)	0.321*** (0.0551)	-1.876*** (0.233)	0.987*** (0.279)	0.198 (0.305)	-0.713 (0.496)
(β_3)Male$_i$	2.009*** (0.117)	— —	2.760*** (0.146)	1.680*** (0.184)	1.189*** (0.221)	2.114*** (0.327)
(γ_1)Age$_{i,t-1}$	-0.136*** (0.00523)	— —	-0.167*** (0.00881)	-0.128*** (0.0101)	-0.116*** (0.0105)	-0.138*** (0.0122)
(γ_2)Tenure$_{i,t-1}$	1.329*** (0.0278)	0.447*** (0.0126)	1.427*** (0.0204)	1.403*** (0.0312)	1.138*** (0.0411)	1.364*** (0.0839)
(γ_3)Tenure$^2_{i,t-1}$	-0.0202*** (0.000699)	-0.00676*** (0.000216)	-0.0207*** (0.000585)	-0.0202*** (0.000844)	-0.0177*** (0.00111)	-0.0222*** (0.00196)
$p(\beta_1+\beta_2=0)$	0.947	0.0000	0.0024	0.00221	0.0464	0.104
$p(\beta_2+\beta_3=0)$	0.0000	—	0.0000	0.0000	0.0000	0.00707
R^2_{Adj}	0.0939	0.131	0.101	0.0997	0.0925	0.0881
#Obs	14,045,092	14,045,092	3,371,062	3,485,689	3,563,700	3,624,641
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

productive female workers, a female leader will be able to assign productive female workers to higher wages and unproductive female workers to lower wages. This causes the empirical results that female executives increase female worker wages at the top, but the reverse is observed at the bottom of the wage distribution.

In a separate strand of literature, the taste-based discrimination theory is based on the model of Becker (1971). The employers discrimination towards an employee is purely taste-based, for instance, based on the employee's gender, rather than performance driven. In this setup, the employer receives a dis-utility from employing workers of the opposite gender. As a direct result, male executives pay women less than they pay equally productive men. Similarly, female executives will engage in a symmetric behavior against men. The result is that a gender wage gap exists, and such gap is a homogeneous gender gap that does not depend on the productivity and other metrics[7].

[7] Additional related theoretical works for private firms include Black (1995); Rosén (2003), and empirical works include Charles and Guryan (2008); Flabbi (2010).

Table 1.15: **Female Executives & Propensity to Promote on Pay Grade, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FExec}_{i,j,t-1}$	0.255 (0. 186)	0.322*** (0.0449)	0.649*** (0. 147)	0.193 (0.238)	-0.350 (0.244)	0.449 (0.569)
$(\beta_2)\text{FExec}_{i,j,t-1} \times \text{Male}_i$	-0.354** (0.148)	-0.368*** (0.0684)	-1215*** (0.141)	0.0256 (0.181)	-0.0782 (0.240)	-0.366 (0.488)
$(\beta_3)\text{Male}_i$	0.759*** (0.0901)	— —	2.457*** (0.0816)	0.520*** (0.113)	0.352*** (0.131)	0.345 (0.283)
$(\gamma_1)\text{Age}_{i,t-1}$	-0.333*** (0.00737)	— —	-0277*** (0.00940)	-0.354*** (0.0108)	-0.329*** (0.0146)	-0.367*** (0.0203)
$(\gamma_2)\text{Tenure}_{i,t-1}$	-0.929*** (0.0353)	0.0183 (0.0188)	-0.939*** (0.0167)	-1.048*** (0.0326)	-0.730*** (0.0460)	-0.964*** (0.103)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	0.0204*** (0.000844)	-0.00726*** (0.000219)	0.0228*** (0.000390)	0.0229*** (0.000755)	0.0151*** (0.00105)	0.0194*** (0.00245)
$p(\beta_1 + \beta_2 = 0)$	0.483	0.367	0.0000	0.333	0.0825	0.821
$p(\beta_2 + \beta_3 = 0)$	0.0054	—	0.0000	0.0006	0.204	0.966
R^2_{Adj}	0.172	0.222	0.190	0.187	0.152	0.172
#Obs	11,253,610	11,253,610	2,962,367	2,853,477	2,592,224	2,845,542
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓
Step FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In addition to the first two theories, there is another separate set of literature that focuses on the complementarities that could affect career outcome of different gender differently. An example is the mentoring story mentioned by Athey, Avery, and Zemsky (2000). A leader can mentor workers of lower rank and increases the productivities of the workers in contact (an executive has an "aura" that covers a limited number of people). Assuming mentoring is more effective if a leader and an employee are of the same gender, then workers who are closer to the executives will receive more mentoring opportunity than workers who are less closer to the executives. Thus, one should expect that for female workers who are at the higher-end of the wage distribution, and for the female workers who are in a smaller office, the effect of female leadership on their wages should be stronger.

From the empirical evidence shown in the previous sections (that the effect of female leadership is stronger when the office is smaller, or when the employee ranking is higher and closer to that of the leaders, or when the leader's ranking is lower and closer to that of the employee), the theoretical model that is consistent with the empirical evidence is the third model that the female leader mentors female workers in contact, thus, these female workers experience the increase in wage, increase in promotion and stay longer in the tenure. Although there is no conclusive evidence to prove the mentorship theory, its theoretical prediction is the most consistent with the empirical observation.

1.6 Robustness Checks

In this study, I employ a variety of robustness checks to validate the empirical findings. For example, I substitute the measurement of female leadership with the historical average of female leadership experienced by a particular person, excluding the impact of him/herself. The result of this historical female leadership is qualitatively the same and quantitatively similar to the tables shown above. I include these results in Tables A.5 and A.6.

Further, I vary the sample of employee status in the wage regression to ensure that not a particular class of employees is driving the results. Specifically, I investigate how female leadership affects non-supervisors and supervisors separately. Again the results are qualitatively the same and quantitatively similar. The corresponding effects are reported in Tables A.3 and A.4.

Moreover, I report the result not only on the full 100% sample, but on a randomly selected 10% subsample that serves as cross-validation to ensure that not a particular subsample is driving the results. Again, the results are qualitatively the same and quantitatively similar, even after the reduction in the sample size that amounts to the attenuation bias. Corresponding results are reported in Tables A.1 and A.2.

Furthermore, I include the career mobility results estimated using the randomly selected 10% sample to demonstrate that the results are sensitive to this choice and are not driven by a particular subset of the sample. Corresponding results are reported in Tables A.7, A.8 and A.9.

1.7 Conclusion

This paper concludes that female bosses help to reduce the gender wage gap and the promotion gap after controlling for all other characteristics in the data. The most plausible reason for such effect can be attributed to the mentoring story, rather than the statistical discrimination or taste-based discrimination. The evidence provided shows that female leadership's effect on the gender wage gap is significantly stronger for offices that are smaller in size and for employees who are already on higher levels of the pay distribution. However, further analysis is needed to confirm the mentorship theory.

Exhibit 1.1: **Example Offices, 10% Sample**

Greenville Offices (top 2 largest):

- Social Security Administration (10 people)
- Veteran and Health Administration (VA) (8 people)

Clemson Offices (top 2 largest):

- Forest Service (USDA) (3 people)
- Agricultural Research Service (USDA) (2 people)

Boston Offices (top 5 largest):

- Veterans Health Administration (VA) (253 people)
- Environment Protection Agency (63 people)
- Transportation Security Administration(43 people)
- Social Security Administration (42 people)
- Internal Revenue Service (DTRS) (40 people)

Top 7 Largest of All Offices:

- National Institute of Health (HHS) (1118 people), Bethesda, Maryland
- Social Security Administration (985 people), Woodlawn , Maryland
- Patent and Trademark Office(COM) (729 people), Alexandria, Virginia
- Department of State (547 people), Washington, District of Columbia
- Veterans Health Administration (VA) (487 people) , Los Angeles, California
- Patent and Trademark Office(COM) (482 people), Arlington, Virginia
- Federal Bureau of Investigation (DOJ), (481 people), Washington, District of Columbia

Figure 1.2: **Female Representation Among Leadership Positions Over Year**

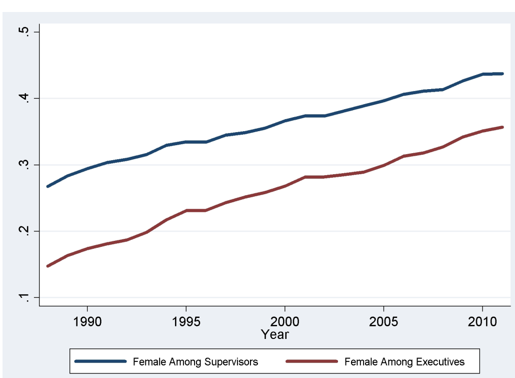


Figure 1.3: **Female Representation in Different Occupation Category Over Time**

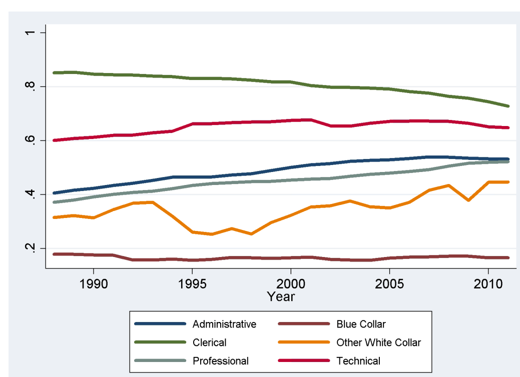


Figure 1.4: **Median Real Basic Pay Over Year**

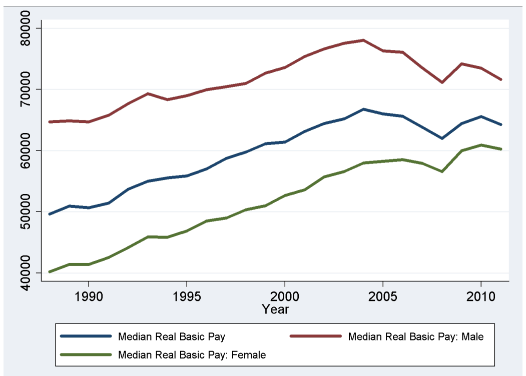


Figure 1.5: **Median Real Basic Pay Over Age**

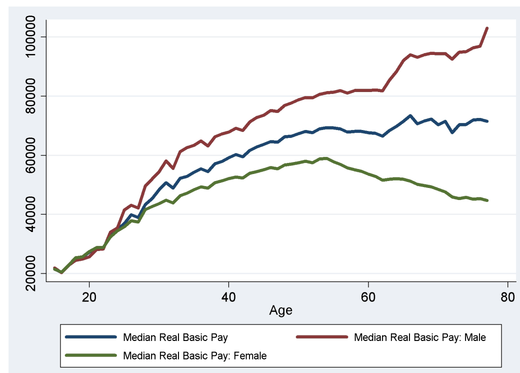
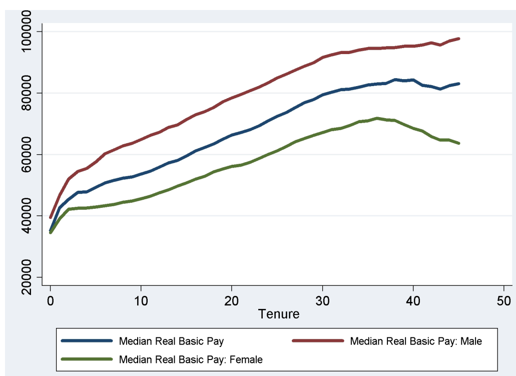


Figure 1.6: **Median Real Basic Pay Over Tenure**



Chapter 2

The Effects of FMLA on Women's Promotion in the Federal Government

Joint work with Patrick Warren

Summary Using the Office of Personnel Management (OPM) data and imputed fertility rates from Centers for Disease Control and Prevention (CDC) data, I examine the effects of the Family Medical Leave Act (FMLA) on the promotion of women into managerial positions. I find that after the FMLA was passed in 1993, there was a significant change in the relationship between fertility and promotion, with fertility becoming more negatively associated with promotion. Compared to the relationship prior to 1993, a 10% increase in fertility is associated with an additional 1.3% decline in the probability of being promoted. This suggests that the FMLA may have inhibited the relative career progress of women in high-fertility demographic groups in the U.S. federal civil service system. [1]

Keywords: Family Medical Leave Act, Office of Personnel Management, female, promotion, fertility

JEL Classification: J16, J31

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2.1 Introduction

In April 2016 New York passed a law requiring up to 12 weeks of partially paid time off for new parents, funded through a weekly payroll tax. The next day, San Francisco became the first city in the U.S. to require employers to offer six weeks of fully paid leave for new parents. Are these policies going to help or harm women's careers? One could imagine myriad impacts of these sorts family-friendly policies throughout the stages of a career: hiring, retention, and promotion. In this paper we want to focus on one aspect of a career, promotion into management or supervisory roles; analyze an important precursor to these more generous policies, the Family Medical Leave Act (FMLA); and do so in a context where it is uniquely possible to carefully trace the progress of large set of employees throughout their careers, in U.S. Federal Civil Service.

Movement into supervisory positions is an important element of career progress. Managerial positions are on top of the career ladder, receive higher salaries, and establish a general managerial set of skills that are valuable in the market, more generally. For example, according to Forbes in 2016, chief executives are among top ten best paying jobs in the US. And it may be particularly important for understanding the relative progress of women. Over the last half century the gender pay gap between men and women has been shrinking, with the strongest wage convergence in the 1980s (Blau and Kahn, 2008). According to Blau and Kahn (2016b), however, between 1980 and 2010 the wage gap fell faster at the bottom than at the top of the distribution, and a large gap remains at the top of the distribution. This exception to the general convergance suggests that some factor remains that differentially affects the entrance of women to the upper echelons of the wage ladder. In this paper, we investigate whether a family-friendly policy like those recently implemented might affect the entry of women into such managerial or supervisory positions. To do so, we look at the impact of a earlier policy that introduced a weaker set of related requirements on employers, the FMLA.

The Family Medical Leave Act was introduced in 1993. It requires all federal government offices, regardless of the number of employees an office has, to provide up to 12 weeks of unpaid leave to an eligible employee while maintaining their current health insurance benefits. Employers are required to return these employees to the same (or equivalent) position as they had prior to taking this leave with equivalent pay, benefits, and other terms and conditions of employment. An employee's use of FMLA leave cannot be counted against the employee under a "no-fault" attendance policy. Employers are also required to continue group health insurance coverage for an employee on FMLA leave under the same terms and conditions as if the employee had not taken leave. To become eligible for FMLA, a federal employee must work for the federal government for at least 12 months[2] prior to the leave and have an eligible reason for the leave. Eligible employees may take up to 12 workweeks of leave in a 12-month period for one or more of the following reasons: the birth of a son or daughter or placement of a son or daughter with the employee for adoption or foster care; to care for a spouse, son, daughter, or parent who has a serious health condition; for a serious health condition that makes the employee unable to perform the essential functions of his or her job; or for any qualifying exigency arising out of the fact that a spouse, son, daughter, or parent is a military member on covered active duty or call to covered active duty status. However, the majority of FMLA leaves occur due to a child birth, and this was one of the major reasons that the FMLA was created. Thus, the majority of people who take FMLA leave are women.

We employ a unique data set from the Office of Personnel Management (OPM) that follows the careers of all civilian federal government employees from 1988 till 2011. The structure of these data is particularly suitable to answer our main question , i.e. how the adoption of the FMLA affects women's promotions into central positions. The OPM data provides us with information on over 3.4 million individuals, on their wages, career progressions, education, benefits, organizations they work, clear job assignments, and other information. Moreover, we can clearly distinguish between promotions into central positions versus promotions into non-supervisory line positions. In our paper we focus only on the promotions into the following categories: Supervisor or Manager, Leader, Team leader, Supervisor (CSRA) and Management Official (CSRA)[3].

The effect of the FMLA on women's promotions is theoretically ambiguous. On the one hand, mandated leave could add a significant cost in promoting a woman to a central position, since the employee may leave for three months due to child birth, but must be guaranteed the opportunity to return to a similar role. Thus, the organization is left unable to fill it with a permanent replacement and must "make do" in the meantime, a risky and costly position to be in. As a result, the FMLA may diminish women's promotion opportunities. An employer making the choice between two identical employees who have only one difference, fertility rate, might choose the one

[2]The 12 months of employment do not have to be consecutive. That means any time previously worked for the same employer (including seasonal work) could, in most cases, be used to meet the 12-month requirement.

[3]The classification is taken from the OPM code-book.

with a lower fertility rate in order to avoid the disruption of a long leave. For example, a man (with zero fertility) or a woman above 40 (with close to zero fertility), may be more attractive than a woman with a high fertility "risk". On the other hand, the FMLA could have a positive effect on women's promotions. For example, the FMLA could strengthen the employees' attachment to the firm, since a pregnant mother knows her job is waiting for her when she returns from her leave. This fact may boost firm-specific or position-specific investments. As a result, the promotion rate for women could rise.

In order to examine the effect of the Family and Medical Leave Act on the likelihood of promotions we exploit the variation in the expected fertility of women . We combine the OPM data with Centers for Disease Control and Prevention natality data on the average number of children born per female by year, race, and age bracket. The idea is that each female worker can be assigned an expected fertility for a woman of her age, race, and year, and we can relate this expected fertility to her chance of promotion, both before and after the passage of the FMLA.

We estimate a linear probability model explaining promotion into managerial (central) positions. The explanatory variable of interest is an interactive term between expected fertility and a dummy variable for 1993-2011 (years in which the FMLA was active). After controlling for age, job tenure (experience), level of education, yearly dummies, age dummies, race dummies, and occupational dummies, we want to know if the relationship between average fertility rates and promotion probabilities changes in the years after the FMLA was implemented and, if so, how much and in which direction.

We find that after the FMLA was passed in 1993, there was a significant change in the relationship between expected fertility and promotion, with expected fertility becoming more negatively associated with promotion. Compared to the relationship prior to 1993, a 10 percentage point increase in expected fertility is associated with an additional 0.86 percentage point decline in the probability of being promoted. This relationship is robust to several definitions of promotions, and suggests that something changed in the years since the FMLA was passed that may have inhibited the relative progress of women in high-fertility demographic groups up through the U.S. federal civil service system. Moreover, if we control for individual fixed effects or employ the hazard model analysis, we get similar results both in the magnitude and the direction. Finally, in the model when we control for individual fixed effects and we run the same model on men matching them with the corresponding female fertility, the coefficient on interactive term between fertility and a dummy variable for 1993-2011 is insignificant.

Our findings align well with Thomas (2015), the only other paper to investigate the relationship between the FMLA and promotions. He investigates how mandated maternity leave policies impact the gender gap in promotions in the private sector. He finds that women hired after the enactment of the FMLA were five percent more likely to remain employed but eight percent less likely to be promoted than those who were hired before the FMLA. He finds that information asymmetry drives the increase in gender gap in promotions. However, Thomas does not have the detailed data on types of promotions; while, we can differentiate between promotions into various supervisory positions and other types of promotions. Thus, we focus solely how the FMLA affects women's promotions into managerial positions. In addition, Thomas looks into the private sector; while, we are focusing on Federal government employees. Finally, Thomas does not have the detailed fertility on women and he uses the assumption that women's fertility after 40 is zero.

2.2 Literature Review

Our analysis contributes to three literatures, in increasing generality. First, we contribute to a large literature on the effects of the FMLA on women. Waldfogel, Higuchi, and Abe (1999) finds that the FMLA had a small, positive effect on leave-taking among employees of medium sized firms (with 100 to 499 employees) but no effect on employees of large firms (500 or more employees). Further, her findings demonstrate no significant effects on employment and wages. Baum (2003)shows that the FMLA induces women to postpone their return to work, but eventually brings more women back to work. Also he found that family leave legislation has not affected overall employment levels or wages among women of childbearing age. Averett and Whittington (2001) investigate other potential effects of the FMLA such as whether maternity leave affects fertility. Their results suggest that women with maternity leave are significantly more likely to give birth. Also they found that the fertility plans do not influence job sorting based on maternity leave benefits.

Second, we contribute to a broader literature on the differential (and sometimes perverse) effects of family-friendliness on women's careers. Klerman and Leibowitz (1999) find that prior to the passage of the statutes, 60% of NLSY mothers who were working full-time before giving birth were working at the same job after giving birth and the fertility plans do not influence job sorting based on maternity leave benefits. Also, the theory suggests that a mother should earn a higher wage at the job that she held before giving birth than at a new job because she can continue to benefit from the firm-specific human capital that she accumulated prior to giving birth (Spalter-Roth, Hartmann, and Andrews, 1993; Waldfogel, 1997, 1998; Klerman and Leibowitz, 1999). argues that maternity leave legislation should not increase wages by improving return-to-work decisions if employers and employees are able to voluntarily negotiate maternity leave provisions without maternity leave legislation. Klerman and Leibowitz (1999) demonstrate that state maternity leave legislation does not have a significant effect on employment. Dalto (1989); Spalter-Roth et al. (1993); Waldfogel (1997) find that women's wages are higher if they were covered by an employer's maternity leave policy voluntarily provided by employers. Baker and Milligan (2008), using Canadian data, find that modest leave entitlements of 17—18 weeks do not change the amount of time mothers spend away from work. In contrast, longer leaves do have a substantive impact on behavior, leading to more time spent at home. Also they find that all entitlement they examined increase job continuity with the pre-birth employer.

Finally, we contribute to a literature on the determinants of the career trajectories of public sector employees. Bolton and de Figueiredo (2017) find that the unconditional gender wage gap in public sector has been large but steadily declining over the time period but almost half the magnitude of the private sector. They show that entry wages for men are higher than entry wages for women in the public sector and promotions are similar for both groups while the wage gap increase during employee's tenure.

2.3 Data and Empirical Analysis

2.3.1 The data

Our primary data on career trajectories come from the OPM federal employment records, which tracks 3.4 unique individuals or 28 million person-year observations. We restrict to those between the ages of 20 and 65 who work full time in non-seasonal jobs and are observed at least twice from 1988-2011 (24 years). These records include information on promotions, wages, work schedules, awards, and supervisory status, as well as demographic and educational information. The main advantage of dataset is that it provides information on the exact career path of the government employees if he or she does not leave the government job. Our dataset is also much larger than Federal Scope Employee cube or Central Personal data releases. In our benchmark model we define a promotion as equal to one if at this point in time a person holds a supervisory position consistent with the OPM code book[4]. In 1993 two separate categories called "Supervisor" and "Manager" were combined into one called "Supervisor or Manager". We code our definition of promotion accordingly. We also use these OPM data to create a number of categorical control variables: age by 5-year ranges, tenure by years in government, occupation by seven occupation classes, race , and six educational categories.

In order to examine the effect of the FMLA on women's promotions into supervisory positions we exploit the variation in the average fertility of women by age, race, and birth year. We impute fertility rates from the CDC natality dataset by calculating the fraction of women of a given age, race, and birth year to give birth in each year. For falsification we also impute a placebo fertility rate for every male in our sample.

Table 1 depicts the percentage of people ever promoted by gender together with the descriptive statistic on the fertility variable. For example, 12.9% of males have been promoted at least once into a central position. Also, the highest probability of having a child is 23.6%.

Table 2.1: **Promotion and Fertility Rates**

Promotion		
	Male	**Female**
% Person-Year Promoted	12.9	9.9
% Person-Year Not Promoted	87.1	90.1
% Person Ever Promoted	14.7	12.5
% Person Ever Not Promoted	99.9	99.9
Fertility		
Mean	—	0.025
Std. Dev.	—	0.039
Max	—	0.236
Min	—	0

Note: Promotion is defined as a change of service status from non-supervisory position into supervisory position

[4]Supervisor or Manager, Leader, Team leader, Supervisor (CSRA) and Management Official (CSRA)*

2.3.2 Empirical Analysis

Using the OPM and the CDC natality data we exploit the fertility variation of women by age, race, and birth year in order to study the effect of the Family Medical Leave Act passed in 1993 on promotions of women into supervisory positions. Our main model is a linear probability model which measures the relationship between the FMLA and promotions of women into supervisory[5] positions. We start with a 10% random sample of 3.4 million individuals.

$$\begin{aligned}\text{Promoted}_{i,t} =& \alpha_i + \beta_1 \text{Fertility}_{i,t} \times \mathbb{I}_{\text{FMLA}} + \beta_2 \text{Fertility}_{i,t} \\ & + \boldsymbol{B}_{\text{educ}} \cdot \boldsymbol{I}_{\text{educ}} + \boldsymbol{B}_{\text{race}} \cdot \boldsymbol{I}_{\text{race}} + \boldsymbol{B}_{\text{age}} \cdot \boldsymbol{I}_{\text{age}} \\ & + \boldsymbol{B}_{\text{year}} \cdot \boldsymbol{I}_{\text{year}} + \boldsymbol{B}_{\text{occp}} \cdot \boldsymbol{I}_{\text{occp}} + \boldsymbol{B}_{\text{tenure}} \cdot \boldsymbol{I}_{\text{tenure}} \\ & + \varepsilon_{i,t} \end{aligned} \tag{2.1}$$

$\text{Promoted}_{i,t}$ is equal to 1 if a person moves into one of the central positions mentioned in previous section and is equal to 0 otherwise. Once a person is promoted they are dropped for subsequent years. We estimate the following equation for a federal government employee i in vectors, $\boldsymbol{B}_{\text{educ}}, \boldsymbol{B}_{\text{race}}, \boldsymbol{B}_{\text{age}}, \boldsymbol{B}_{\text{year}}, \boldsymbol{B}_{\text{occp}}$ and $\boldsymbol{B}_{\text{tenure}}$ are vectors of education, race, year, occupation, and tenure fixed effects. The parameter of interest is β_1,which is the coefficient on the interaction term between fertility and dummy variable for the year the FMLA is active (1993-2011). Intuitively, it measures how the relationship between fertility and probability of promotion changes in the years after the FMLA was implemented. The thought experiment is to think about pairs of women, one high anticipated fertility and one low anticipated fertility, alike in all other characteristics, and see if their promotion rates are different and, in turn, whether that difference changes in the post-FMLA years.

We also include a with-employee estimate, Model 2 ,which is the same as Model 1 but we add individual fixed effects. The thought experiment here is different. It asks, among women who are promoted, whether their promotion is more likely to occur in high- or low- anticipated fertility years, controlling for other characteristics, and whether that relationship changes in the years after the FMLA is implemented.

[5]In our paper we use “supervisory position”, “managerial position” or “central position” interchangeably.

Table 2.2: **The Relationship between Anticipated Fertility and Promotion for Women, before and after FMLA Adoption**

	Model 1		Model 2	
	Coefficient	Std. Err.	Coefficient	Std. Err.
Fertility$_{i,t}$ * $\mathbb{I}_{\text{FMLA}}$	-0.0858***	0.0177	-0.0381**	0.018
Fertility$_{i,t}$	0.2248***	0.035	0.1531***	0.033
Education:				
No Bachelors	-0.002***	0.0007	0.0045	0.0029
Bachelors	0.0267***	0.001	0.0186***	0.0038
Masters	0.0493***	0.0013	0.0683***	0.0046
Professional Degr.	0.0899***	0.0022	0.1035***	0.0115
Advanced Cert.	0.099***	0.01	0.1048***	0.0351
PhD	0.0753***	0.0026	0.0995***	0.0117
—	—	—	—	—
Individual FEs	×		✓	

Note: Linear probability model. ***:0.001, **:0.01, *:0.05

The results of these two analyses are presented in Table 2. Considering first Model 1, the coefficient of interest β_2 is significant and negative. It says that in the years after the FMLA was implemented women with 10 percentage points higher anticipated fertility in a year are about 0.9 percentage points less likely to be promoted in that year than they would have been in the pre-FMLA years.

Model 2 tells a very similar story, where the promoted women are less likely to be promoted in high-anticipated-fertility years in the post-FMLA era than they are in the pre-FMLA era. Women with 10 percentage points higher anticipated fertility in a given year are about 0.2 percentage points less likely to receive their promotion in that year.

It is important to note, in interpreting these relationships, is that anticipated fertility has a very strong direct, positive relationship to promotion. We put no causal interpretation on the direct relationship between anticipated fertility and promotion, however, as it merely indicates that, on average, anticipated fertility is positive correlated with factors that are valuable in supervisory positions. Nevertheless, we believe it's reasonable to put a causal interpretation on our interaction, since FMLA is unlikely to affect the cost or benefits of non-fertility-related factors that are correlated with anticipated fertility.

The major threat to identification for out interaction effect, we believe, is actually not omitted variables that are correlated with anticipated fertility but rather omitted variables that are correlated with FMLA adoption. Since FMLA adoption is only identified in the time series, we worry

Table 2.3: **The Relationship between Placebo Anticipated Fertility and Promotion for Men, before and after FMLA Adoption**

	Model 1	
	Coefficient	Std. Err.
$\text{Fertility}_{i,t} * \mathbb{I}_{\text{FMLA}}$	-0.02	0.023
$\text{Fertility}_{i,t}$	0.1	0.05
Education:		
No Bachelors	0.002	0.002
Bachelors	0.037***	0.002
Masters	0.064***	0.003
Professional Degr.	0.094***	0.003
Advanced Cert.	0.017	0.016
PhD	0.088***	0.004
—	—	—
Individual FEs	✓	

Note: Linear probability model. ***:0.001, **:0.01, *:0.05

that other changes in federal government policy or practice at the same time could have affected the promotion rates along dimensions that are correlated with anticipated fertility. To address this concern, we repeat the analysis above for a subset of employees for which the taking up of FMLA benefits should not be related to female fertility rates, men. Thus, if the change in the relationship between anticipated fertility and promotion in the post-FMLA period is actually being driven by other factors that are correlated with anticipated fertility, we should see that relationship for those workers, too. In fact, when we use placebo fertility for men, we see no relationship between fertility and promotion in either period, suggesting that fertility may, in fact, have been the proper channel.

2.4 Conclusion

We find that women in high fertility cohort/years have career trajectories that are negatively affected by the FMLA, i.e women with higher fertility are less likely to be promoted into supervisory or managerial positions after the enactment of the FMLA. In particular, a 10 percentage point increase in expected fertility is associated with an additional 0.86 percentage point decline in a promotion rate in the model without fixed effects. As we mentioned earlier the result is robust to different definitions of promotions which suggests that something changed in the years since FMLA was passed that may have inhibited the relative progress of women in high-fertility demographic groups in the federal government system.

Chapter 3

Does Medicaid Expansion Increase Fertility? Evidence under Alternative Insurance

Joint work with Scott Barkowski

Summary This paper investigates the effect of Medicaid expansion on the fertility rate using individual level panel data under alternative insurance. We find that without controlling for an alternative insurance, Medicaid eligibility expansion has no significant effect on female fertility. However, we find that for those females not covered by insurance, Medicaid eligibility increases fertility by 5 percentage points per year over time. Such effect is both statistical and economically significant and is stronger among groups of females that are un-married or not employed. These evidence suggests that Medicaid program as a social benefit is more effective for those who need it the most.

Keywords: Medicaid expansion, fertility, fixed effects, Cox survival model

JEL Classification: J16, J31

3.1 Introduction

Beginning in 1984, eligibility for Medicaid expanded dramatically for pregnant women and children. During the same period, the U.S. fertility rate rose and the abortion rate declined. It is a natural question to ask: does Medicaid expansion increase fertility? What makes this question more relevant today is the increased role of Medicaid. In 2007 over 13% of the total U.S. population was covered by Medicaid (U.S. Census Bureau, 2008), and even more of the population is eligible but currently not enrolled. Medicaid has covered over one-third of births in years since the 1990s expansions were completed (Cutler and Gruber, 1996b). Moreover, due to the recent uncertainties around the Patient Protection and Affordable Care Act ("PPACA") the subsidized insurance coverage could be revoked. These recent developments call for a timely investigation of the effect of Medicaid on fertility in order to understand the potential policy implications.

In this paper, we employ a unique identification strategy to estimate the effect of Medicaid expansion on fertility. There are three distinguishing features of our approach that allow for more reliable causal inference than previous studies. First, we use individual level data rather than state-level aggregate data. This corrects for the bias induced by aggregation. For example, suppose Medicaid has no effect on fertility, and during the period of Medicaid expansion only those who are not eligible for Medicaid had increased fertility, while those who are eligible did not. In this scenario one would observe, in aggregate data, an increase in total fertility and an increase in Medicaid coverage. Second, we consider the effect of an alternative insurance which further corrects for the bias induced by substitution. For example, Medicaid as a health insurance benefit should only provide incentive if a female is not already covered by an alternative insurance. If during the Medicaid expansion women, who are actually benefiting from Medicaid, have no fertility changes; while women, who are eligible but would not benefit from Medicaid (due to an alternative insurance), have increased in fertility, then one may draw the conclusion that Medicaid eligibility increases fertility, while it actually does not. Third, we track individual for multiple periods over time, which aligns individuals' future fertility to the same set of individuals' Medicaid eligibility, rather than different set of individuals' eligibility, and further encompasses the delayed effect on fertility in response to Medicaid eligibility.

Our results show that Medicaid eligibility, for those females who can actually benefit from it (do not have an alternative insurance), increases fertility rate by 5 percentage points a year over time. The effect is statistically and economically significant, and the increase of fertility rate is almost linearly proportional over time. Without considering an alternative insurance, there are no statistical or economically significant effect of Medicaid eligibility on fertility. Moreover, when we breakdown the sample by different groups, we find that for females that are unmarried, or unemployed the effect of Medicaid eligibility on fertility is particularly strong relative to females that are married or employed. These evidence suggests that the Medicaid program as an aid is more effective for those who need it the most.

The rest of the paper is organized as follows: section 3.2 reviews the background of the study and the existing literature; section 3.3 summarizes our data and variables; section 3.4 discusses in detail the empirical identification and estimation strategy and presents the main results of the paper; section 3.5 discusses the robustness checks; section 3.6 concludes.

3.2 Background and Literature

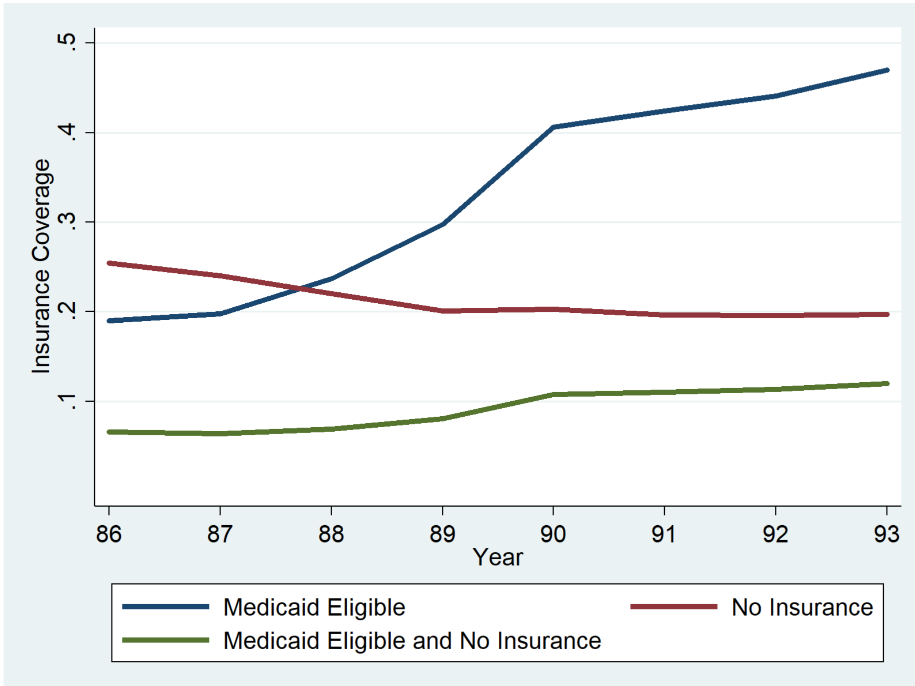
3.2.1 The Expansion of Medicaid Eligibility in the U.S.

As pointed out by Cutler and Gruber (1996b), the expansion of the Medicaid program has been one of the most important changes in the health insurance market in the United States. Traditionally, Medicaid coverage among the low income families was limited to recipients of AFDC (Aid to Families with Dependent Children) program, which effectively limited to single women with children and below half of the poverty line. However, the eligibility was expanded beyond AFDC recipients. Expansion over time occurred at different rates across states and across different demographic groups. By 1992, individuals with income below 100 percent or more of the poverty line are covered, with some states expanding up to 185 percent below the poverty line.

Figure 3.1 depicts the expansion of Medicaid coverage. It is produced using our data in terms of fraction of eligible women. It shows that between 1988 and 1991, the coverage of Medicaid increased sharply[1].

[1]Similar pattern is also observed in Zavodny and Bitler (2010) which illustrates the expansion of Medicaid in terms of income threshold

Figure 3.1: **The Expansion of Medicaid**



3.2.2 Theoretical Mechanisms of Medicaid and Fertility

The purpose of Medicaid as an insurance benefit program is unambiguous; its ex-ante economic impact, however, is less clear. The total effects of Medicaid on fertility could result from mechanisms of opposite signs. For example, one might view that Medicaid expansions have a positive effect on birth rates: the reduction in health care costs lowers the total cost of a child, thus should increase the number of children; or the reduction in health care costs effectively raises income (net of such costs) should increase the number of children; or as noted by Hotz, Klerman, and Willis (1997), increases in income, that are not due to increases in women's earnings, have a positive, but small effect on fertility. Yet, other economic mechanisms, on the contrary, imply that Medicaid expansions have a negative effect on birth rates. For example, Medicaid expansions could increase women's labor force participation, and higher labor force participation could lead to lower birth rates; if the expansions improved child health outcomes, parents might have opted to have fewer births as the "quality versus quantity" trade-off in Becker (1960); Also, the expansions also may have increased some women's access to family planning, reducing unwanted births. One can also potentially believe that there are no significant effects on birth rates by Medicaid simply because eligible women were unaware of or did not respond to the changes in legislature.

3.2.3 Empirical Literature

In an attempt to address the causal relationship between Medicaid expansion and the empirically observed increase in birth rate, one has to go beyond a simple correlation analysis. Previous literature on the topic has sought to answer this question, but the empirical methods were unsatisfactory and results were rather contradictory.

The literature has empirically documented an increase in fertility rate during the Medicaid expansion. For example, in the study of Joyce, Kaestner, and Kwan (1998), they use the pooled regressions over 15 state level data, and concluded that Medicaid expansion is associated with a 5% increase in the birthrate among white women, while no relationship among black women, and no evidence on the abortion rate due to inadequate data. The procedure is simply regressing the logarithms of abortion rates or birthrates on the indicator of two phases of expansion. The regression on aggregated variables may reduce the idiosyncratic noise and thus increase the power of the test, yet the design is only able to address the question to the extent of "statistical association", subject to potentially serious missing variable biases. The state level data is unable address whether the positive association between Medicaid expansion and fertility increase is due to some missing variable or not. One example of this is eligibility: if Medicaid expansion is the main driver behind fertility increase, then Medicaid should have effect only on woman who are eligible, and no effect on woman who are not eligible. Therefore, an increase in fertility for non-eligible woman should not be considered as effect of Medicaid. The data used has no information on the individual's eligibility to Medicaid, rendering the procedure unable to address the core issue: does Medicaid provide positive incentive for woman to give birth?

In a later paper, Zavodny and Bitler (2010) analyze the National Center for Health Statistics (NCHS) dataset with 50 states from 1982 to 1996 and they address the lack of information on the eligibility by examining whether state-level birth and abortion rates are related to the extent of states Medicaid eligibility expansions and the fraction of women eligible for Medicaid. They find little evidence that the Medicaid expansions led to changes in birth rates or abortion rates. However, among white women who have not completed high school, Medicaid expansions boosted the birth rate, controlling for economic and demographic factors. This approach addresses the eligibility at the aggregate state-level, but still unable to control for alternative insurance.

In a more recent paper and the closest to our paper, DeLeire, Lopoo, and Simon (2007) conclude, in contradiction to Joyce et al. (1998), that there is no statistical significant effect from Medicaid expansion to fertility. In this paper the authors restrict the focus on the effects on ”net fertility”, the likelihood of a women having a child. The ”net fertility” differs from ”total fertility” in the sense that changes in ”net fertility” includes both change of demand for children (total fertility), as well as the timing for giving birth. They use the 1985 to 1996 data from National Center for Health Statistics (NCHS) for birth rates and the Current Population Survey (CPS) for a measure of the generosity of state Medicaid programs. They categorized women into 44 cells based on their age,education, marital status, demographic characteristics, and created a ”simulated eligibility” measure and allocate them into the 44 cells. Thus allowing a certain degree of inference on the causal relationship. Yet, their data have no information if women have health insurance already and they can not link women over time to observe actual changes in birth rates. In contrast, in our paper we observe individuals over time and we can see if a child is born a year or more after the Medicaid eligibility. Finally, we know if a woman has already another insurance when she becomes eligible for Medicaid.

3.3 Data and Variables

In this section we discuss in detail the data used in this paper and the construction of the variables.

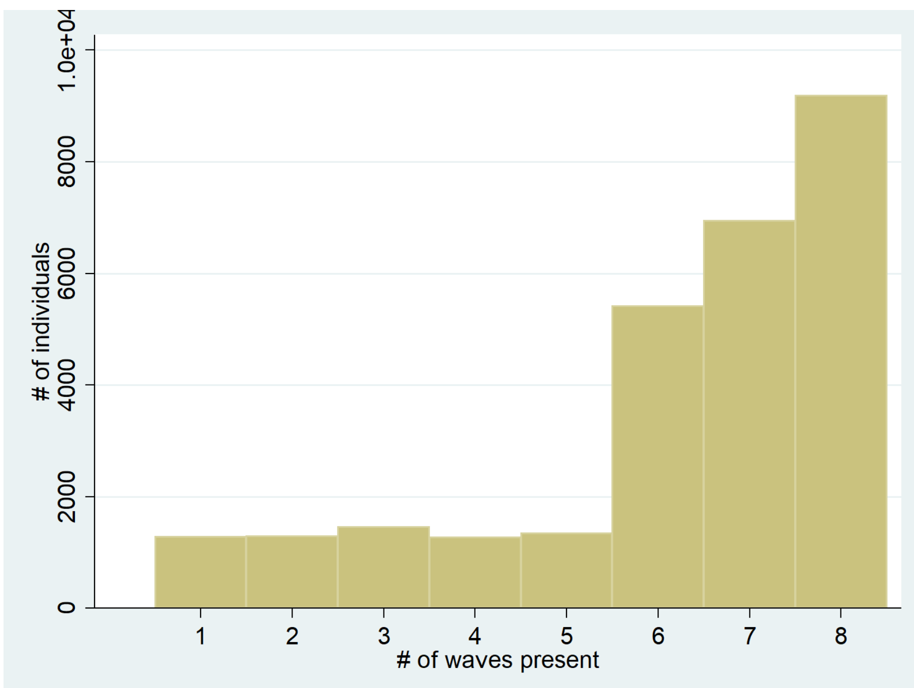
3.3.1 SIPP Panel Waves

The data is used from the Survey of Income and Program Participation (SIPP). SIPP is a household-based survey designed as a continuous series of national panels. Each panel contains a nationally representative sample interviewed every four months over the life of this panel. Such four-month-long subdivision is called a ”wave”. The number of waves varies from panel to panel. We use panels from 1986 till 1991. Each panel surveys completely different individuals. We use panels which last at least two years; in other words, each panel has at least six waves. For example, 1986 and 1987 panels has seven waves; while 1988 panel has six waves and 1990 and 1991 panels have eight waves. For example, if an individual is from panel 1991, she will appear in our data eight times (once in each of the eight waves) every four months, i.e she is followed for two years and 8 months till 1993. In this study, we use the same data as in Barkowski (2014). Existing research that also uses the same dataset includes Currie and Gruber (1996a,b) Cutler and Gruber (1996a) Cutler and Gruber (1996b) Gruber and Yelowitz (1999) Gruber and Simon (2008)

3.3.2 Variable Construction

In this study, we restrict the sample to females who, at the time the first wave of the panel was surveyed, are between the age of 15 to 44, and are the only reproductive female in the household, and do not have an infant. We track these individuals over time and construct their fertility variables, insurance coverage and eligibility as well as other human capital variables. Figure 3.2 reports the distribution of number of waves a female is present in the sample. Majority of the individuals are present in the sample for six or more waves, as the SIPP survey aims to.

Figure 3.2: **Histogram of Number of Waves Present**



Our primary dependent variable of interest is the cumulative birth rate: $\text{Birth}_{i,t\rightarrow t+h}$ which is an indicator variable for whether the individual will give birth in the following h months, with horizons determined by the survey panel waves $h = 0, 4, 8, 12, 16$.

To compare with the literature and perform sanity check, we compute the cumulative fertility rate over time and plot in the following Figure 3.3 which reports the cumulative fertility computed in our sample of females. We see that the annualized (approximately 3 panel waves after the first wave) General Fertility Rate (GFR) is approximately 0.0714, which is close to the statistics of 67.3-70.9 per 1000 female reported by Center for Disease Control and Prevention (CDC) data for the period between 1988-1992. On the bottom panel, I also report the cumulative fertility rate for different demographic groups. Specifically, we see that unemployed or married female have higher fertility rate than average.

Our primary explanatory variable of interest is the state-level imputed individual eligibility for the Medicaid program: $\text{Elig}_{i,t}$ indicates whether individual i at time t is eligible for Medicaid. This variable is constructed using Gruber and Yelowitz (1999) instruments. The eligibility data is taken from Barkowski (2014), and the approach follows that of Cutler and Gruber (1996a,b); Gruber and Yelowitz (1999); Gruber and Simon (2008)

Our next explanatory variable of interest is the individual level of an alternative insurance. We construct the variable $\text{NoIns}_{i,t}$ to indicate that a female does not have an alternative insurance at the time the survey was conducted.

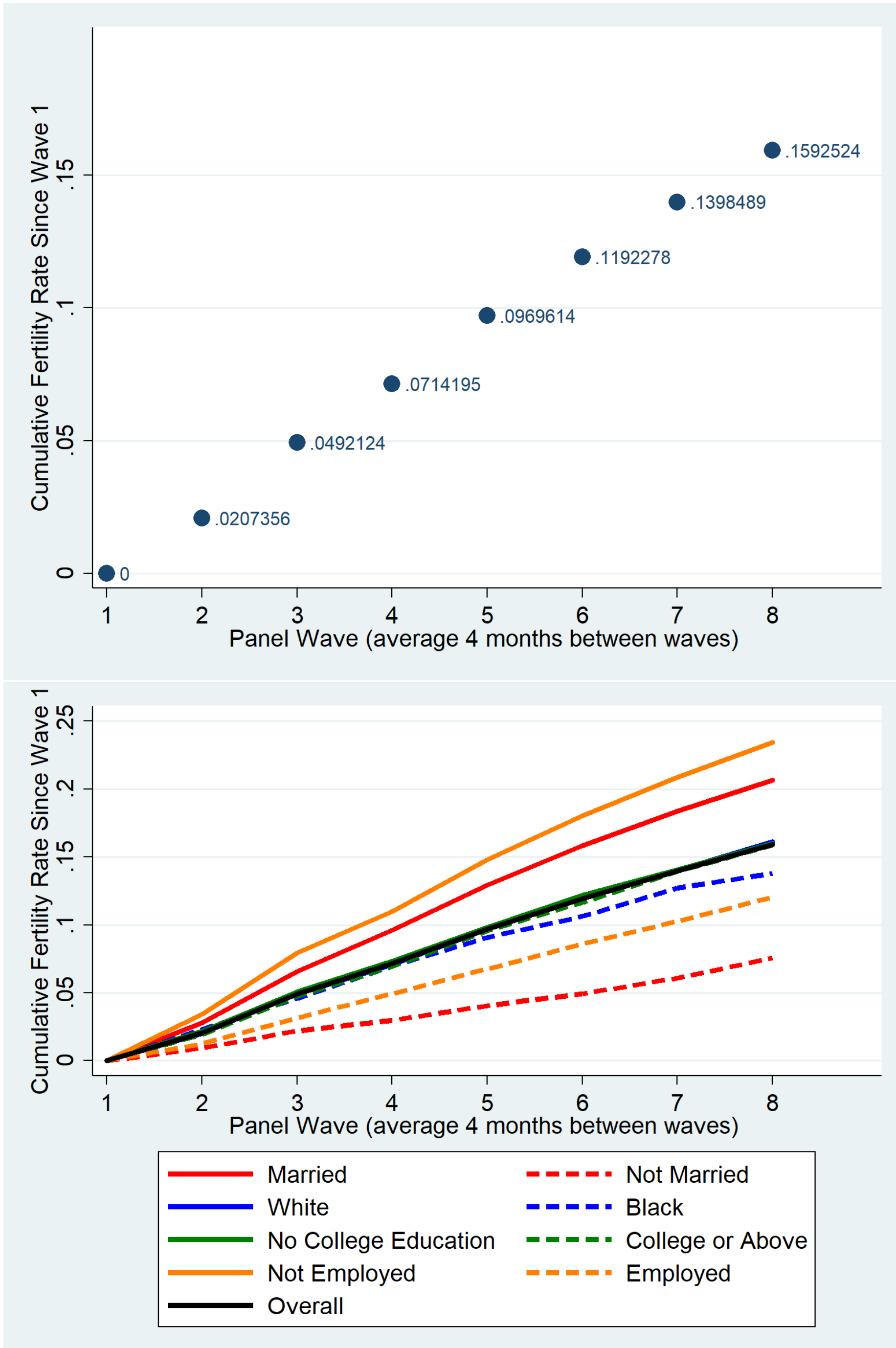
We further use the following categorical variables to control for group fixed effects: race_i classifies the female into white, black, American Indian and Asian categories; kid5_i indicates whether the female has a kid under five years old; and kid17_i indicates whether the female has a kid under 17 years old; year-month_i is the year and month when the survey is conducted; state_i is the state the person is at; $\text{age}_{i,t}$ is an individual's age; $\text{educ}_{i,t}$ is the level of education a person received, classified into no high school degree, high school degree, some college education, and college and above; $\text{Emp}_{i,t}$ indicates whether a female is employed or not.

Table 3.1 reports the averages of the primary variables of interest by marital status, race, education, and employment.

3.4 Empirical Framework

In this section, we discuss the several empirical strategies we take to identify the effect of Medicaid eligibility on fertility. We present the results which demonstrate that when controlling for an alternative insurance and other individual characteristics, Medicaid eligibility in fact has a

Figure 3.3: **Cumulative Fertility Rate over Time**



positive effect on female fertility.

Table 3.1: **Summary Statistics by Demographic Groups**

	Birth$_{i,t\rightarrow t+h}$ (%)					Insurance (%)			# Obs
	$h=0$	$h=4$	$h=8$	$h=12$	$h=16$	Elig$_{i,t}$	NoIns$_{i,t}$	Both$_{i,t}$	
Total	0.070	0.084	0.098	0.111	0.125	0.337	0.212	0.092	174,752
By Marital Status									
Un-Married	0.030	0.035	0.043	0.051	0.060	0.382	0.328	0.146	65,377
Married	0.095	0.113	0.131	0.147	0.163	0.310	0.143	0.059	109,375
By Race									
Black	0.064	0.077	0.090	0.102	0.112	0.372	0.386	0.172	19,316
White	0.071	0.084	0.098	0.112	0.125	0.332	0.187	0.081	149,455
By Education									
No College Education	0.070	0.084	0.098	0.111	0.123	0.421	0.301	0.145	92,684
College or Above	0.071	0.084	0.099	0.112	0.127	0.242	0.111	0.032	82,068
By Employment									
Not Employed	0.106	0.125	0.139	0.148	0.156	0.371	0.377	0.166	63,311
Employed	0.050	0.061	0.076	0.091	0.108	0.318	0.118	0.050	111,441

Sample is restricted to females during reproductive age (15-44), who do not have an infant, are the only reproductive females in households at the time of first wave of the panels. There are a total of 28,221 unique females and a total of 174,752 person-wave observations. Elig$_{i,t}$ is the state-level eligibility calculated using Gruber and Yelowitz (1999) instrument.

3.4.1 Identification Strategy in the Presence of Alternative Insurance

Medicaid, as an insurance aid, may alter the fertility decisions of a woman if she does not have an alternative insurance. However, if one already has an insurance coverage which provides similar or identical benefits as the Medicaid, it is unlikely that the expansion of Medicaid will have any impact on the women's fertility decisions. Therefore, we also aim to identify the potential effects of Medicaid in the presence of alternative insurance.

Specifically, we formulate the following breakdown in Table 3.2 based on the Medicaid eligibility and alternative insurance coverage. We should expect the effect for only the individuals who are covered by Medicaid while having no other alternative insurance.

Table 3.2: **Groups based on Medicaid Eligibility and Alternative Insurance Coverage**

		No Insurance Coverage	
		0	1
Medicaid Eligibility	1	A: No Effect	B: Group Expect Effect
	0	C: No Effect	D: No Effect

To estimate the impact of Medicaid eligibility change from non-eligible to eligible is to compute the following difference-in-difference estimate:

$$\begin{aligned} DiD = & \underbrace{(B-D)}_{\text{Effect of Interest}} - \underbrace{(A-C)}_{\text{Adjust for Medicaid Diff.}} \\ = & \beta_3, \end{aligned}$$

where β_3 is the regression coefficient from the following full interaction fixed-effect model in Equation (3.1),

$$\begin{aligned} \text{Birth}_{i,t\to t+h} = & \alpha + \beta_1 \text{Elig}_{i,t} + \beta_2 \text{NoIns}_{i,t} + \beta_3 \text{Elig}_{i,t} \times \text{NoIns}_{i,t} \\ & + \sum \gamma^j \delta^j_{i,t} + e_{i,t}, \end{aligned} \tag{3.1}$$

where $\text{Birth}_{i,t\to t+h}$ is the cumulative fertility rate of a women from time t to h months later, $\text{Elig}_{i,t}$ and $\text{NoIns}_{i,t}$ are the Medicaid eligibility (the state-level eligibility calculated using Gruber and Yelowitz (1999) instrument) and no alternative health insurance coverage. The group fixed effect variables include race,full interaction between kid5 and kid17, year-month, state, full interaction between age and educ, and state-year.

The relative fertility estimates in terms of coefficients β's are $B = \beta_1 + \beta_2 + \beta_3$, $D = \beta_2$, $A = \beta_1$ and $C = 0$. Thus the fertility effect of switching from not Medicaid eligible to Medicaid eligible in the presence of alternative insurance is β_3.

3.4.2 Group Fixed Effect: Base Case

To establish the base case results, we first estimate the 3.1 model using group fixed effects on pooled individual and panel waves data for $h = 4, 8, 12, 16$. For comparison, we included the coefficient estimates for the case where only Medicaid Eligibility was used in the regression.

Table 3.3 reports the estimation results of this regression. We see that without controlling for alternative insurance, the Medicaid eligibility is statistically insignificant in explaining future fertility across all 4,8,12,16 months. However, once we controlled for the presence of alternative insurance, the Medicaid eligibility has significant positive effect for those who do not already have insurance. This demonstrates the results that Medicaid as a health care benefit do have effect for those individuals who need them. The fertility rate four months in the future for a female who does

Table 3.3: **Group Fixed Effect: Base Case**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LHS = $\text{Birth}_{i,t\to t+h}$	$h=4$	$h=4$	$h=8$	$h=8$	$h=12$	$h=12$	$h=16$	$h=16$
$(\beta_1)\text{Elig}_{i,t}$	0.00490	-0.000453	0.00617	-0.00528	0.00405	-0.0138	0.0114	-0.0120
	(0.0113)	(0.0111)	(0.0239)	(0.0245)	(0.0328)	(0.0333)	(0.0399)	(0.0419)
$(\beta_2)\text{NoIns}_{i,t}$		-0.00529		-0.0130**		-0.0204**		-0.0220**
		(0.00328)		(0.00581)		(0.00775)		(0.0103)
$(\beta_3)\text{Elig}_{i,t} \times \text{NoIns}_{i,t}$		0.0152**		0.0325**		0.0499***		0.0649**
		(0.00664)		(0.0125)		(0.0180)		(0.0254)
# Obs.	118251	118251	99088	99088	79984	79984	60962	60962
Adjusted R^2	0.019	0.019	0.039	0.039	0.055	0.055	0.071	0.071
Group FEs	✓	✓	✓	✓	✓	✓	✓	✓

Sample is restricted to females during reproductive age (15-44), who does not have an infant, are the only reproductive female in the household, at the time of first wave of the panels; There are a total of 28,221 unique females and a total of 174,752 person-wave observation. The group fixed effects terms include race, kid5##kid17, year-month, state, age##educ, state×year. $\text{Elig}_{i,t}$ is the state-level eligibility calculated using Gruber and Yelowitz (1999) instrument
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

not have an infant in the current wave is increased by 1.52% if she becomes eligible for Medicaid and currently does not have an alternative insurance. The same number is increased to 3.25%, 4.99% and 6.49% in 8, 12, and 16 months respectively. However, as we increase the horizon, the number of observations usable to estimate the model drops as our survey only tracks individual up to 8 waves and some households move and disappear from the survey.

3.4.3 Group Fixed Effect by Marital Status

Next we consider the group fixed effect model on different demographic groups to assess the effects of Medicaid expansion on fertility of different groups. We start by investigating the differences across marital status.

Table 3.4 reports the coefficient estimates of equation (3.1) on two sets of samples: married and unmarried. One can see that overall, for married females, the effect of Medicaid eligibility under no insurance is stronger on longer horizons, where it becomes significant on 8 and above horizons. However, for unmarried females the same effect is significant even at the four months horizon.

Table 3.4: **Group Fixed Effect: By Marital Status**

LHS = $\text{Birth}_{i,t\to t+h}$	(1) $h=4$	(2) $h=4$	(3) $h=8$	(4) $h=8$	(5) $h=12$	(6) $h=12$	(7) $h=16$	(8) $h=16$
Married								
$(\beta_1)\text{Elig}_{i,t}$	0.0102	0.00728	0.00339	-0.00400	-0.00386	-0.0172	0.0107	-0.00559
	(0.0156)	(0.0161)	(0.0335)	(0.0341)	(0.0437)	(0.0441)	(0.0529)	(0.0545)
$(\beta_2)\text{NoIns}_{i,t}$		0.000185		-0.00484		-0.0127		-0.0118
		(0.00407)		(0.00724)		(0.0101)		(0.0138)
$(\beta_3)\text{Elig}_{i,t}\times\text{NoIns}_{i,t}$		0.0111		0.0286*		0.0511**		0.0642**
		(0.00898)		(0.0146)		(0.0216)		(0.0290)
# Obs.	74505	74505	62556	62556	50595	50595	38638	38638
Adjusted R^2	0.030	0.030	0.064	0.064	0.092	0.092	0.120	0.120
Un-Married								
$(\beta_1)\text{Elig}_{i,t}$	0.0120	0.000793	0.0373*	0.0187	0.0494*	0.0269	0.0571	0.0278
	(0.0111)	(0.0100)	(0.0200)	(0.0177)	(0.0261)	(0.0234)	(0.0366)	(0.0336)
$(\beta_2)\text{NoIns}_{i,t}$		-0.000385		0.000540		0.00357		0.00990
		(0.00311)		(0.00563)		(0.00729)		(0.00962)
$(\beta_3)\text{Elig}_{i,t}\times\text{NoIns}_{i,t}$		0.0220**		0.0353**		0.0418**		0.0538**
		(0.00866)		(0.0144)		(0.0188)		(0.0251)
# Obs.	43746	43746	36532	36532	29389	29389	22324	22324
Adjusted R^2	0.017	0.019	0.036	0.038	0.051	0.054	0.072	0.076
Group FEs	✓	✓	✓	✓	✓	✓	✓	✓

Sample is restricted to females during reproductive age (15-44), who do not have an infant, are the only reproductive female in the household at the time of first wave of the panels. There are a total of 28,221 unique females and a total of 174,752 person-wave observations. The group fixed effects include race, full interactions between kid5 and kid17, year-month, state, full interaction between age and educ, state-year. $\text{Elig}_{i,t}$ is the state-level eligibility calculated using Gruber and Yelowitz (1999) instrument.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.4.4 Group Fixed Effect: By Race

Next, we estimate the model by comparing between white and black racial groups. Since in the sample American Indian and Asian groups only represent less than 3% of the sample, we exclude them from the model. Still white categories constitute majority of the sample.

Table 3.5 reports the coefficient estimates. Comparing with 3.3, we see that the white category represents the majority of the sample which is in line with the estimates pooling all races together. However, it is particularly noteworthy that for the black category the Medicaid eligibility does not seem to have a significant effect on fertility in the future. This is not only reflected by the fact that the coefficient estimates are not significant for black categories, but also the fact that for the white category the coefficient estimates have increased compared to Table 3.3.

Table 3.5: **Group Fixed Effect: By Race**

LHS = $\text{Birth}_{i,t\to t+h}$	(1) $h=4$	(2) $h=4$	(3) $h=8$	(4) $h=8$	(5) $h=12$	(6) $h=12$	(7) $h=16$	(8) $h=16$
White								
$(\beta_1)\text{Elig}_{i,t}$	0.00731	0.00192	0.0101	-0.00255	0.00692	-0.0128	0.0190	-0.00703
	(0.00987)	(0.00998)	(0.0227)	(0.0239)	(0.0315)	(0.0334)	(0.0352)	(0.0384)
$(\beta_2)\text{NoIns}_{i,t}$		-0.00872***		-0.0210***		-0.0304***		-0.0341***
		(0.00312)		(0.00558)		(0.00823)		(0.0113)
$(\beta_3)\text{Elig}_{i,t} \times \text{NoIns}_{i,t}$		0.0182***		0.0425***		0.0643***		0.0839***
		(0.00663)		(0.0127)		(0.0203)		(0.0296)
# Obs.	102928	102928	86277	86277	69653	69653	53079	53079
Adjusted R^2	0.020	0.020	0.042	0.042	0.058	0.058	0.075	0.075
Black								
$(\beta_1)\text{Elig}_{i,t}$	-0.0131	-0.0222	-0.0253	-0.0367	-0.0286	-0.0357	-0.0609	-0.0696
	(0.0325)	(0.0354)	(0.0656)	(0.0731)	(0.0837)	(0.0991)	(0.108)	(0.122)
$(\beta_2)\text{NoIns}_{i,t}$		0.000579		0.000295		-0.00229		0.00158
		(0.00857)		(0.0158)		(0.0233)		(0.0291)
$(\beta_3)\text{Elig}_{i,t} \times \text{NoIns}_{i,t}$		0.0136		0.0170		0.0109		0.0122
		(0.0171)		(0.0314)		(0.0520)		(0.0618)
# Obs.	11502	11502	9616	9616	7757	7757	5913	5913
Adjusted R^2	0.023	0.023	0.064	0.064	0.093	0.092	0.118	0.118
Group FEs	✓	✓	✓	✓	✓	✓	✓	✓

Sample is restricted to females during reproductive age (15-44), who do not have an infant, are the only reproductive female in the household at the time of first wave of the panels. There are a total of 28,221 unique females and a total of 174,752 person-wave observations. The group fixed effects include race, full interactions between kid5 and kid17, year-month, state, full interaction between age and educ, state-year. $\text{Elig}_{i,t}$ is the state-level eligibility calculated using Gruber and Yelowitz (1999) instrument.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.4.5 Group Fixed Effect By Education

We further investigate the effect of Medicaid expansion on fertility by breaking down the sample into different categories according to education. Rather than including a dummy variable in the regression, we estimate the full model separately on two sets of data, "no college education" and "college or above".

Table 3.6 reports the model coefficients for females with different level of education. On a grand scheme, females, who have college or above education, without an alternative insurance and without Medicaid eligibility, have significantly lower fertility. However, the same does not apply for females with no college education. For females with college or above education, the effect of Medicaid under no insurance has large magnitude of 12.7%

Table 3.6: **Group Fixed Effect: By Education**

LHS = $\text{Birth}_{i,t\to t+h}$	(1) $h=4$	(2) $h=4$	(3) $h=8$	(4) $h=8$	(5) $h=12$	(6) $h=12$	(7) $h=16$	(8) $h=16$
No College Education								
$(\beta_1)\text{Elig}_{i,t}$	0.0192 (0.0128)	0.0155 (0.0127)	0.0309 (0.0267)	0.0222 (0.0276)	0.0400 (0.0378)	0.0294 (0.0387)	0.0337 (0.0490)	0.0187 (0.0502)
$(\beta_2)\text{NoIns}_{i,t}$		-0.000773 (0.00379)		-0.00508 (0.00705)		-0.00571 (0.0102)		-0.00822 (0.0142)
$(\beta_3)\text{Elig}_{i,t}\times\text{NoIns}_{i,t}$		0.00885 (0.00753)		0.0209 (0.0143)		0.0246 (0.0217)		0.0359 (0.0313)
# Obs.	61529	61529	51608	51608	41690	41690	31801	31801
Adjusted R^2	0.020	0.020	0.042	0.042	0.058	0.058	0.076	0.076
College or Above								
$(\beta_1)\text{Elig}_{i,t}$	-0.00271 (0.0166)	-0.00525 (0.0167)	-0.0113 (0.0306)	-0.0171 (0.0313)	-0.0295 (0.0443)	-0.0433 (0.0455)	-0.00276 (0.0532)	-0.0250 (0.0557)
$(\beta_2)\text{NoIns}_{i,t}$		-0.0104** (0.00442)		-0.0223** (0.00849)		-0.0402*** (0.0108)		-0.0465*** (0.0152)
$(\beta_3)\text{Elig}_{i,t}\times\text{NoIns}_{i,t}$		0.0150 (0.0147)		0.0336 (0.0305)		0.0773* (0.0444)		0.127* (0.0642)
# Obs.	56722	56722	47480	47480	38294	38294	29161	29161
Adjusted R^2	0.020	0.020	0.041	0.042	0.060	0.060	0.077	0.077
Group FEs	✓	✓	✓	✓	✓	✓	✓	✓

Sample is restricted to females during reproductive age (15-44), who do not have an infant, are the only reproductive female in the household at the time of first wave of the panels. There are a total of 28,221 unique females and a total of 174,752 person-wave observations. The group fixed effects include race, full interactions between kid5 and kid17, year-month, state, full interaction between age and educ, state-year. $\text{Elig}_{i,t}$ is the state-level eligibility calculated using Gruber and Yelowitz (1999) instrument.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.4.6 Group Fixed Effect: By Employment

We further investigate the effect of Medicaid expansion on fertility by breaking down the sample into different categories according to employment status. Rather than including a dummy variable in the regression, we estimate the full model separately on two sets of data, "Not employed" and "employed".

Table 3.7 reports the coefficient estimated using the two sets of sample on employment. As we can see that females who are not employed are more affected by the Medicaid insurance eligibility under no insurance than female who are employed. The difference not only comes in terms of statistical significance but also present in terms of the magnitude. The point estimates of the β_3 coefficients are 1.93%, 3.76% 5.98% and 8.61% respectively for 4,8,12,16 month horizons.

Table 3.7: **Group Fixed Effect: By Employment**

LHS = $\text{Birth}_{i,t\to t+h}$	(1) $h=4$	(2) $h=4$	(3) $h=8$	(4) $h=8$	(5) $h=12$	(6) $h=12$	(7) $h=16$	(8) $h=16$
Not Employed								
$(\beta_1)\text{Elig}_{i,t}$	-0.00278	-0.0129	-0.00930	-0.0292	-0.0309	-0.0633	-0.0213	-0.0694
	(0.0198)	(0.0206)	(0.0409)	(0.0461)	(0.0524)	(0.0568)	(0.0674)	(0.0732)
$(\beta_2)\text{NoIns}_{i,t}$		-0.00996*		-0.0191*		-0.0289**		-0.0355**
		(0.00558)		(0.00970)		(0.0110)		(0.0151)
$(\beta_3)\text{Elig}_{i,t} \times \text{NoIns}_{i,t}$		0.0193*		0.0376*		0.0598**		0.0861**
		(0.0110)		(0.0219)		(0.0229)		(0.0326)
# Obs.	39360	39360	33209	33209	26986	26986	20725	20725
Adjusted R^2	0.032	0.032	0.060	0.061	0.075	0.076	0.093	0.094
Employed								
$(\beta_1)\text{Elig}_{i,t}$	0.0118	0.0112	0.0184	0.0147	0.0273	0.0186	0.0397	0.0270
	(0.00993)	(0.0101)	(0.0212)	(0.0218)	(0.0290)	(0.0297)	(0.0348)	(0.0365)
$(\beta_2)\text{NoIns}_{i,t}$		-0.00952***		-0.0208***		-0.0301***		-0.0321***
		(0.00264)		(0.00585)		(0.00776)		(0.0103)
$(\beta_3)\text{Elig}_{i,t} \times \text{NoIns}_{i,t}$		0.00247		0.0172		0.0395**		0.0576**
		(0.00552)		(0.0123)		(0.0189)		(0.0259)
# Obs.	78891	78891	65879	65879	52998	52998	40237	40237
Adjusted R^2	0.014	0.015	0.033	0.033	0.050	0.050	0.068	0.068
Group FEs	✓	✓	✓	✓	✓	✓	✓	✓

Sample is restricted to females during reproductive age (15-44), who do not have an infant, are the only reproductive female in the household at the time of first wave of the panels. There are a total of 28,221 unique females and a total of 174,752 person-wave observations. The group fixed effects include race, full interactions between kid5 and kid17, year-month, state, full interaction between age and educ, state-year. $\text{Elig}_{i,t}$ is the state-level eligibility calculated using Gruber and Yelowitz (1999) instrument.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.5 Robustness Checks

In this section, we perform a selection of robustness checks. We vary the methodology by using individually imputed eligibility in place of the Gruber and Yelowitz (1999) instrument for state level Medicaid eligibility. Also we employ the Cox (1972) survival model on individual level.

3.5.1 Group Fixed Effect: Imputed Eligibility

First we investigate if the results are sensitive to the choice of the Medicaid eligibility instruments. Previously, we used the Gruber and Yelowitz (1999) instrument for state-level Medicaid eligibility, while in this section we use the individual level imputed eligibility $\text{ImpElig}_{i,t}$ according to Barkowski (2014). We present the base case regression in Table 3.8 to compare against Table 3.3. As expected, Medicaid eligibility has significant effect on females who do not have alternative insurance. The β_3 term is significantly positive across all horizons. Notice that without controlling

Table 3.8: **Group Fixed Effect: Imputed Eligibility**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$h = 4$	$h = 4$	$h = 8$	$h = 8$	$h = 12$	$h = 12$	$h = 16$	$h = 16$
(β_1)ImpElig$_{i,t}$	-0.00495***	-0.00935***	-0.0119***	-0.0196***	-0.0196***	-0.0288***	-0.0256***	-0.0382***
	(0.00105)	(0.00116)	(0.00189)	(0.00198)	(0.00265)	(0.00312)	(0.00320)	(0.00425)
(β_2)NoIns$_{i,t}$		-0.00433*		-0.00787		-0.00597		-0.000212
		(0.00252)		(0.00486)		(0.00673)		(0.00888)
(β_3)ImpElig$_{i,t}$ $\times$NoIns$_{i,t}$		0.0130***		0.0229***		0.0245***		0.0278***
		(0.00250)		(0.00538)		(0.00791)		(0.00953)
# Obs.	118251	118251	99088	99088	79984	79984	60962	60962
Adjusted R^2	0.019	0.019	0.039	0.039	0.055	0.056	0.072	0.073
Group FEs	✓	✓	✓	✓	✓	✓	✓	✓

Sample is restricted to females during reproductive age (15-44), who do not have an infant, are the only reproductive female in the household at the time of first wave of the panels. There are a total of 28,221 unique females and a total of 174,752 person-wave observations. The group fixed effects include race, full interactions between kid5 and kid17, year-month, state, full interaction between age and educ, state-year. Elig$_{i,t}$ is the state-level eligibility calculated using Gruber and Yelowitz (1999) instrument.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

for the alternative insurance term, the estimate of the effect of Medicaid eligibility will be severely biased.

3.5.2 Cox Survival Model

Finally, as an additional robustness check, we implement the Cox (1972) proportional hazard model to investigate the women's decisions to give birth.

One may view that giving birth to the first child is different from giving birth to another child when the female already has given birth before; therefore, these two births should not be treated equally. Moreover, one may also be concerned that females, who are never going to give birth, represent significant portion of the population, as such their presence could affect the model estimates in linear regression. In light of this, we construct a time2baby variable that tracks each individual's time till giving birth to a child in the sample. We use the Cox and Oakes (1984) method to control for covariates. We keep only the females that given birth in the sample period.

We examine the survival function for a women to remain in the no-birth-yet category. Table 3.9 reports the Cox proportional hazard model estimates for un-adjusted and adjusted for alternative insurance. The results show that Medicaid eligibility seems to increase females fertility (causing them to drop out of the "no-birth-yet" category faster). The point estimate for eligible for Medicaid and without insurance is 3.63% although statistically insignificant.

Figure 3.4: **Survival Function**

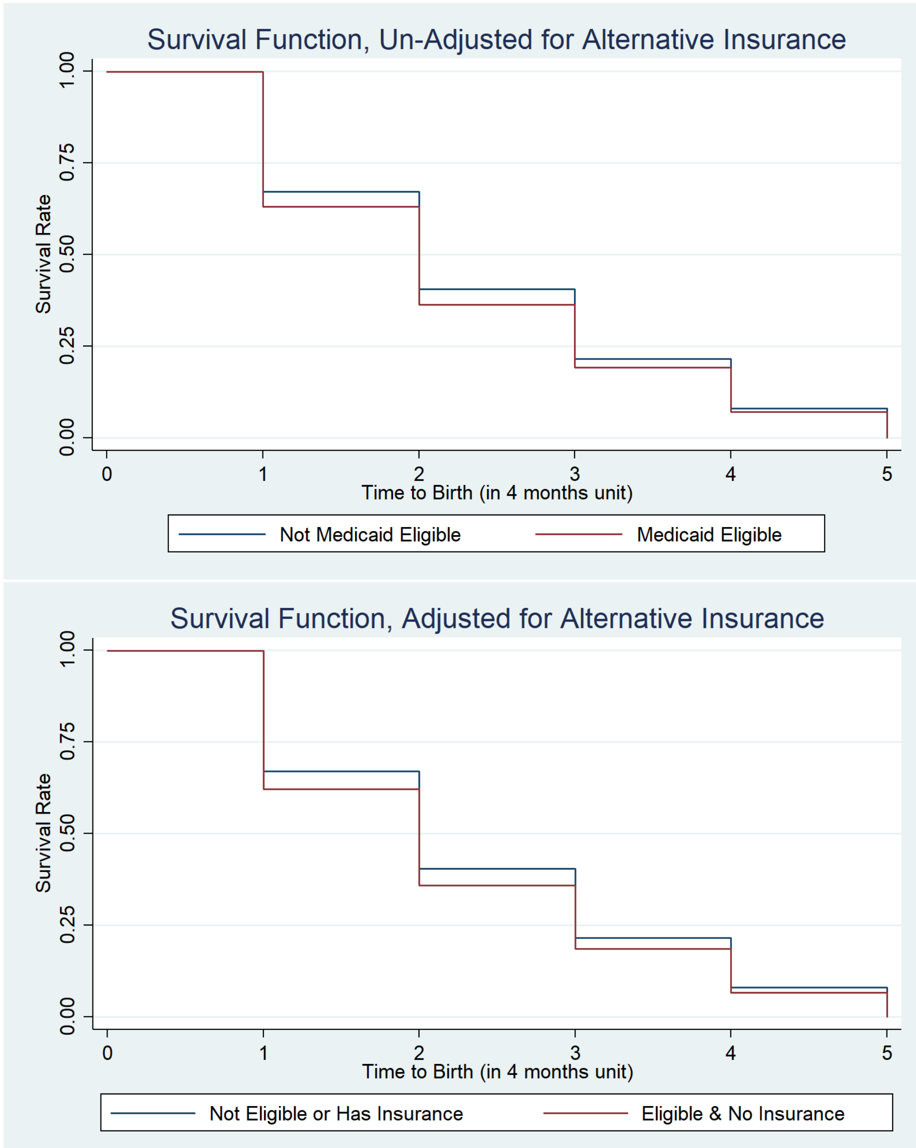


Figure 3.4 reports the survival function over time in units of four months for the un-adjusted model and model controlled for insurance. Females who are eligible for Medicaid remain in the "no-birth-yet" category shorter. By controlling for an alternative insurance, we see that the group of female who are eligible and no insurance are remaining in the "no-birth-yet" category even shorter, consistent with the previously reported estimate that Medicaid eligibility for those who are not coverage by insurance has more effect in increasing female fertility.

It is worth noting that due to data limitations, we are only able to observe a consistent

Table 3.9: **Cox Proportional Hazard Estimate**

	(1) Model 1	(2) Model 2
$\text{ImpElig}_{i,t}$	0.0602***	0.0325
	(0.0137)	(0.0218)
$\text{NoIns}_{i,t}$		0.00811
		(0.0179)
$\text{ImpElig}_{i,t} \times \text{NoIns}_{i,t}$		0.0363
		(0.0312)
Observations	32541	32541

Sample is restricted to females during reproductive age (15-44), who does not have an infant, are the only reproductive female in the household, at the time of first wave of the panels; $\text{ImpElig}_{i,t}$ is the individual-level eligibility calculated using Barkowski (2014) approach.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

panel of female for only up to 8 panel waves. With only 8 observations, we are not able to estimate the effect with a high level of statistical precision using the survival model.

3.6 Conclusion

In summary, we use individual level panel data with eligibility to Medicaid as well as an alternative insurance coverage to investigate the effect of Medicaid expansion on fertility. By comparing a model without considering alternative insurance, we show that the presence of alternative insurance interferes with the effect of Medicaid eligibility on female fertility. Specifically, without controlling for insurance, one cannot conclude that Medicaid eligibility increases or decreases the female fertility; however, after controlling for the presence of an alternative insurance, the females who are eligible for Medicaid but have no alternative insurance increase their fertility significantly over all horizons ranging 4,8,12, and 16 months. By separately estimating the models into different demographic groups, we see that unmarried, white, with college or above education, not employed females are more impacted by the Medicaid eligibility as a potential health care benefit.

Appendices

Appendix A

Appendix for Chapter 1

A.1 Data Cleaning Details

I follow the general approach in cleaning the data as in Bolton and de Figueiredo (2017). Since the dataset is very large, I take a conservative approach in data cleaning. In my analysis, I remove observations that are prone to error, such as an individual changed gender or race, missing service status and missing duty stations. I also restrict the sample to be only on full-time employees. I also dropped offices which had less than 3 employees on average over the observed years.

A.2 Additional Tables and Figures

Figure A.1: **Distribution of Tiny Office Sizes**

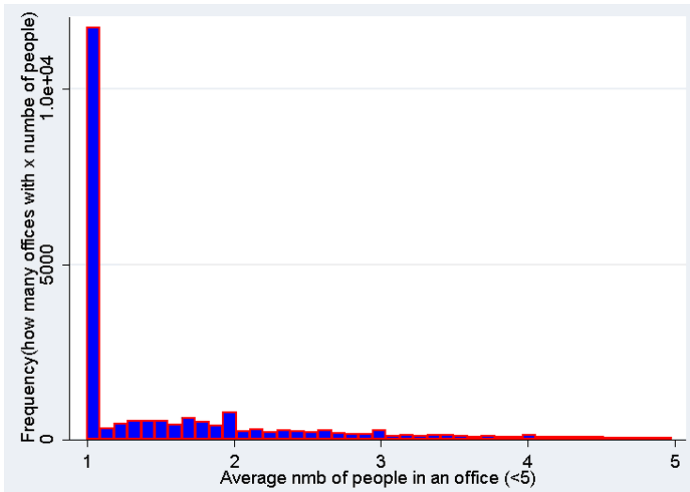


Figure A.2: **Distribution of Office Sizes**

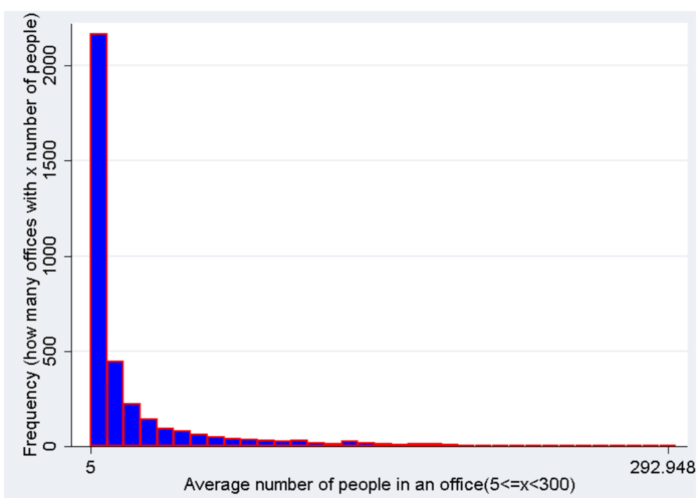


Table A.1: **Female Supervisors & log(Basic Pay), All Service Status, 10% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t-1}$	4.715*** (0.425)	1.273*** (0.139)	3.774*** (0.406)	3.588*** (0.784)	4.403*** (1.335)	11.00*** (3.369)
$(\beta_2)\text{FSup}_{i,j,t-1} \times \text{Male}_i$	-10.99*** (0.616)	-1.436*** (0.207)	-9.490*** (0.548)	-8.588*** (1.199)	-10.69*** (2.398)	-14.90*** (3.038)
$(\beta_3)\text{Male}_i$	9.788*** (0.358)	— —	10.86*** (0.314)	9.093*** (0.641)	8.093*** (1.154)	12.14*** (1.590)
$(\gamma_1)\text{Age}_{i,t-1}$	0.261*** (0.0154)	— —	0.226*** (0.0195)	0.230*** (0.0216)	0.266*** (0.0286)	0.293*** (0.0417)
$(\gamma_2)\text{Tenure}_{i,t-1}$	1.647*** (0.0332)	1.282*** (0.0290)	1.869*** (0.0374)	1.714*** (0.0487)	1.423*** (0.0413)	1.699*** (0.0984)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	-0.0196*** (0.000856)	-0.0301*** (0.000327)	-0.0213*** (0.000961)	-0.0215*** (0.00123)	-0.0161*** (0.00100)	-0.0213*** (0.00254)
$p(\beta_1 + \beta_2 = 0)$	1.92e-42	0.277	2.12e-43	8.39e-08	0.000732	0.283
$p(\beta_2 + \beta_3 = 0)$	0.00511	—	0.00293	0.494	0.0601	0.105
R^2_{Adj}	0.724	0.702	0.705	0.723	0.759	0.729
#Obs	1334109	1334109	321137	335961	334387	342624
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

10% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: **Female Supervisors & Propensity to Promote on Pay Grade, 10% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t-1}$	0.272 (0.589)	-0.918 (0.627)	-1.107 (1.125)	0.948 (0.973)	-0.655 (1.303)	1.231 (1.231)
$(\beta_2)\text{FSup}_{i,j,t-1} \times \text{Male}_i$	0.663 (0.689)	2.528*** (0.857)	1.761 (1.439)	0.690 (1.285)	-1.071 (1.327)	0.210 (1.416)
$(\beta_3)\text{Male}_i$	0.0188 (0.450)	— —	-0.415 (0.865)	0.689 (0.815)	1.010 (0.755)	-1.273 (0.895)
$(\gamma_1)\text{Age}_{i,t-1}$	-0.489*** (0.0531)	— —	-0.551*** (0.0962)	-0.368*** (0.107)	-0.460*** (0.120)	-0.536*** (0.112)
$(\gamma_2)\text{Tenure}_{i,t-1}$	-1.103*** (0.0719)	-0.937*** (0.225)	-1.195*** (0.140)	-1.010*** (0.139)	-1.099*** (0.146)	-1.067*** (0.137)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	0.0205*** (0.00166)	0.0225*** (0.00353)	0.0224*** (0.00329)	0.0179*** (0.00307)	0.0214*** (0.00364)	0.0200*** (0.00303)
$p(\beta_1 + \beta_2 = 0)$	0.0783	0.00585	0.553	0.0691	0.101	0.191
$p(\beta_2 + \beta_3 = 0)$	0.251	—	0.281	0.182	0.957	0.396
R^2_{Adj}	0.165	0.335	0.172	0.161	0.156	0.194
#Obs	97798	97798	33939	21835	19216	22808
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓	✓
Step FE	✓	✓	✓	✓	✓	✓

10% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: **Female Supervisors & log(Basic Pay), Non-Supervisors, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t-1}$	5.437*** (0.440)	2.128*** (0.0598)	1.747*** (0.170)	6.616*** (1.083)	11.22*** (2.342)	14.57** (7.072)
$(\beta_2)\text{FSup}_{i,j,t-1} \times \text{Male}_i$	-11.25*** (0.723)	-1.500*** (0.0943)	-3.355*** (0.256)	-15.33*** (1.219)	-18.17*** (3.061)	-19.98*** (4.002)
$(\beta_3)\text{Male}_i$	8.358*** (0.373)	— —	6.998*** (0.137)	10.68*** (0.535)	10.72*** (1.382)	12.35*** (1.935)
$(\gamma_1)\text{Age}_{i,t-1}$	0.262*** (0.0105)	— —	0.216*** (0.00633)	0.213*** (0.0116)	0.272*** (0.0174)	0.279*** (0.0324)
$(\gamma_2)\text{Tenure}_{i,t-1}$	1.640*** (0.0226)	1.454*** (0.00848)	1.985*** (0.0145)	1.736*** (0.0308)	1.438*** (0.0315)	1.593*** (0.0685)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	-0.0231*** (0.000545)	-0.0341*** (0.000101)	-0.0289*** (0.000348)	-0.0246*** (0.000713)	-0.0198*** (0.000704)	-0.0226*** (0.00172)
$p(\beta_1 + \beta_2 = 0)$	3.34e-33	1.63e-18	5.28e-15	2.06e-13	0.0113	0.452
$p(\beta_2 + \beta_3 = 0)$	4.57e-10	—	2.85e-76	1.04e-09	0.0000201	0.000866
R^2_{Adj}	0.726	0.705	0.719	0.719	0.756	0.735
#Obs	13,153,420	13,153,420	3,117,388	3,255,052	3,370,187	3,410,793
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: **Female Supervisors & log(Basic Pay), Supervisors, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t-1}$	4.919***	3.160***	7.662***	-0.100	-2.167	-7.018
	(0.573)	(0.151)	(0.348)	(1.385)	(2.932)	(12.54)
$(\beta_2)\text{FSup}_{i,j,t-1} \times \text{Male}_i$	-6.525***	-2.906***	-8.991***	-4.763***	0.659	-0.164
	(0.665)	(0.194)	(0.467)	(1.077)	(2.303)	(2.244)
$(\beta_3)\text{Male}_i$	8.243***	—	9.820***	7.221***	5.096***	5.312***
	(0.266)	—	(0.219)	(0.429)	(0.959)	(0.922)
$(\gamma_1)\text{Age}_{i,t-1}$	0.411***	—	0.341***	0.391***	0.439***	0.436***
	(0.0157)	—	(0.0135)	(0.0200)	(0.0261)	(0.0469)
$(\gamma_2)\text{Tenure}_{i,t-1}$	0.657***	0.889***	0.994***	0.651***	0.617***	0.527***
	(0.0328)	(0.0175)	(0.0331)	(0.0441)	(0.0661)	(0.0775)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	-0.00141**	-0.0200***	-0.00583***	-0.000388	-0.00191	-0.0000817
	(0.000561)	(0.000246)	(0.000697)	(0.000889)	(0.00129)	(0.00129)
$p(\beta_1 + \beta_2 = 0)$	0.00184	0.0291	0.00000300	0.000216	0.584	0.558
$p(\beta_2 + \beta_3 = 0)$	0.000187	—	0.0174	0.000641	0.0000510	0.000563
R^2_{Adj}	0.541	0.685	0.469	0.509	0.599	0.603
#Obs	2592918	2592918	730869	694471	568375	599203
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: **Female Supervisor History & log(Basic Pay), All Service Status, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
(β_1)FSupHist$_{i,j,t-1}$	5.335*** (0.513)	5.007*** (0.128)	4.538*** (0.278)	4.984*** (0.861)	5.203*** (1.382)	4.467* (2.386)
(β_2)FSupHist$_{i,j,t-1}$ $\times$ Male$_i$	-16.05*** (0.749)	-3.899*** (0.188)	-9.032*** (0.353)	-18.62*** (1.063)	-19.24*** (2.408)	-19.71*** (3.022)
(β_3)Male$_i$	11.07*** (0.308)	— —	10.06*** (0.145)	12.52*** (0.425)	11.82*** (1.007)	12.85*** (1.364)
(γ_1)Age$_{i,t-1}$	0.266*** (0.0115)	— —	0.219*** (0.00677)	0.225*** (0.0128)	0.278*** (0.0185)	0.283*** (0.0367)
(γ_2)Tenure$_{i,t-1}$	1.684*** (0.0238)	1.408*** (0.00808)	2.002*** (0.0153)	1.780*** (0.0306)	1.473*** (0.0310)	1.665*** (0.0774)
(γ_3)Tenure$^2_{i,t-1}$	-0.0203*** (0.000582)	-0.0315*** (0.0000938)	-0.0246*** (0.000356)	-0.0214*** (0.000692)	-0.0175*** (0.000687)	-0.0211*** (0.00194)
$p(\beta_1+\beta_2=0)$	2.86e-78	1.28e-15	1.73e-44	7.26e-41	5.51e-13	0.000000672
$p(\beta_2+\beta_3=0)$	2.99e-20	—	0.0000881	1.78e-17	0.000000570	0.000362
R^2_{Adj}	0.721	0.710	0.712	0.712	0.752	0.732
#Obs	16109577	16109577	3948016	4021001	4050616	4089944
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: **Female Executive History and log(Basic Pay), All Service Status, 100% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
(β_1)FExecHist$_{i,j,t-1}$	0.897** (0.359)	0.747*** (0.0585)	2.413*** (0.211)	0.909* (0.481)	0.282 (0.668)	0.787 (1.141)
(β_2)FExecHist$_{i,j,t-1} \times$ Male$_i$	-4.970*** (0.480)	-0.903*** (0.0906)	-6.568*** (0.258)	-4.799*** (0.657)	-2.906*** (1.018)	-4.317*** (1.480)
(β_3)Male$_i$	6.274*** (0.226)	— —	8.718*** (0.114)	6.977*** (0.256)	4.579*** (0.379)	5.894*** (0.727)
(γ_1)Age$_{i,t-1}$	0.267*** (0.0114)	— —	0.218*** (0.00676)	0.226*** (0.0128)	0.280*** (0.0186)	0.287*** (0.0362)
(γ_2)Tenure$_{i,t-1}$	1.685*** (0.0236)	1.408*** (0.00808)	2.003*** (0.0152)	1.783*** (0.0308)	1.472*** (0.0311)	1.668*** (0.0763)
(γ_3)Tenure$^2_{i,t-1}$	-0.0202*** (0.000582)	-0.0315*** (0.0000938)	-0.0246*** (0.000356)	-0.0213*** (0.000696)	-0.0173*** (0.000692)	-0.0209*** (0.00194)
$p(\beta_1 + \beta_2 = 0)$	1.75e-23	0.0250	2.37e-74	2.00e-11	0.00266	0.00893
$p(\beta_2 + \beta_3 = 0)$	0.00468	—	1.63e-22	0.000211	0.0497	0.225
R^2_{Adj}	0.720	0.710	0.712	0.711	0.751	0.731
#Obs	16105631	16105631	3944614	4020567	4050523	4089927
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

100% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: **Female Supervisors & Propensity to Promote Into Supervisory Status, 10% Data**

	(1)	(2)	Office Size Quartile			
	Office FE	Ind. FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t-1}$	1.77*** (0.492)	0.946*** (0.326)	3.38*** (0.705)	0.333 (0.934)	0.0232 (1.18)	2.18 (2.78)
$(\beta_2)\text{FSup}_{i,j,t-1} \times \text{Male}_i$	-7.67*** (0.689)	-1.76*** (0.535)	-11.6*** (0.893)	-4.49*** (1.45)	-2.34 (1.96)	-2.09 (2.83)
$(\beta_3)\text{Male}_i$	4.95*** (0.380)	— —	6.48*** (0.514)	3.05*** (0.766)	2.27** (1.03)	2.88** (1.44)
$(\gamma_1)\text{Age}_{i,t-1}$	-0.131*** (0.0140)	— —	-0.197*** (0.0308)	-0.0742*** (0.0278)	-0.144*** (0.0246)	-0.124*** (0.0291)
$(\gamma_2)\text{Tenure}_{i,t-1}$	1.33*** (0.0409)	0.448*** (0.0425)	1.61*** (0.0583)	1.25*** (0.0627)	1.08*** (0.0622)	1.45*** (0.107)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	-0.0211*** (0.00110)	-0.00642*** (0.00755)	-0.0241*** (0.00178)	-0.0183*** (0.00181)	-0.0174*** (0.00177)	-0.0252*** (0.00258)
$p(\beta_1 + \beta_2 = 0)$	2.11e-25	0.0528	4.79e-30	0.000130	0.155	0.976
$p(\beta_2 + \beta_3 = 0)$	7.01e-10	—	5.94e-12	0.123	0.953	0.610
R^2_{Adj}	0.0938	0.132	0.111	0.0977	0.0842	0.0905
#Obs	1177390	1177390	264847	298260	306037	308246
Ind. FE	—	✓	—	—	—	—
Office FE	✓	—	✓	✓	✓	✓
Race, OccGrp FE	✓	—	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓	✓

10% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: **Female Supervisors & Propensity to Exit, 10% Data**

	(1)	Office Size Quartile			
	Office FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t-1}$	0.632 (0.425)	0.594** (0.254)	0.594 (0.462)	-0.998 (0.660)	6.341 (7.873)
$(\beta_2)\text{FSup}_{i,j,t-1} \times \text{Male}_i$	0.0113 (0.214)	-0.232 (0.290)	-0.121 (0.446)	1.095* (0.588)	0.249 (0.594)
$(\beta_3)\text{Male}_i$	0.219** (0.109)	0.309** (0.143)	0.424* (0.221)	-0.289 (0.277)	-0.0216 (0.327)
$(\gamma_1)\text{Age}_{i,t-1}$	0.176*** (0.0116)	0.198*** (0.0188)	0.194*** (0.0220)	0.203*** (0.0228)	0.123*** (0.0236)
$(\gamma_2)\text{Tenure}_{i,t-1}$	-0.699*** (0.0193)	-0.703*** (0.0327)	-0.650*** (0.0320)	-0.706*** (0.0347)	-0.723*** (0.0457)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	0.0231*** (0.000553)	0.0238*** (0.000951)	0.0216*** (0.000957)	0.0230*** (0.00107)	0.0237*** (0.00125)
$p(\beta_1 + \beta_2 = 0)$	0.0840	0.178	0.327	0.890	0.389
$p(\beta_2 + \beta_3 = 0)$	0.102	0.747	0.285	0.0257	0.482
R^2_{Adj}	0.0538	0.0597	0.0499	0.0532	0.0573
#Obs	1030199	260197	252813	245242	271947
Office FE	✓	✓	✓	✓	✓
Race, OccGrp FE	✓	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓
Step FE	✓	✓	✓	✓	✓

10% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9: **Female Supervisors & Propensity to Exit, Full Interactions, 10% Data**

	(1)	Office Size Quartile			
	Office FE	Size (1)	Size (2)	Size (3)	Size (4)
$(\beta_1)\text{FSup}_{i,j,t}$	0.113 (1.104)	0.438 (0.787)	0.134 (1.182)	-3.751*** (1.428)	6.087 (11.33)
$(\beta_2)\text{GS}_{i,t}$	-0.0502*** (0.00459)	-0.0422*** (0.00490)	-0.0541*** (0.00605)	-0.0720*** (0.00939)	-0.0483** (0.0227)
$(\beta_3)\text{Male}_i$	2.771*** (0.431)	3.827*** (0.623)	1.988** (0.890)	2.022* (1.077)	3.135** (1.319)
$(\beta_4)\text{FSup}_{i,j,t} \times \text{GS}_{i,t}$	0.00879 (0.00842)	0.00278 (0.00740)	0.00789 (0.0102)	0.0383** (0.0149)	0.0113 (0.0472)
$(\beta_5)\text{FSup}_{i,j,t} \times \text{Male}_i$	-0.0794 (0.860)	-1.140 (1.256)	1.684 (1.746)	0.829 (2.160)	-0.895 (2.569)
$(\beta_6)\text{GS}_{i,t} \times \text{Male}_i$	-0.0193*** (0.00378)	-0.0287*** (0.00549)	-0.0107 (0.00752)	-0.0131 (0.00938)	-0.0198 (0.0125)
$(\beta_7)\text{FSup}_{i,j,t}$ $\times\text{GS}_{i,t} \times \text{Male}_i$	-0.00581 (0.00791)	0.00612 (0.0112)	-0.0231 (0.0155)	-0.0142 (0.0191)	-0.00709 (0.0268)
$(\gamma_1)\text{Age}_{i,t-1}$	0.165*** (0.0117)	0.184*** (0.0188)	0.183*** (0.0223)	0.190*** (0.0225)	0.114*** (0.0253)
$(\gamma_2)\text{Tenure}_{i,t-1}$	-0.777*** (0.0179)	-0.796*** (0.0313)	-0.716*** (0.0323)	-0.817*** (0.0339)	-0.769*** (0.0405)
$(\gamma_3)\text{Tenure}^2_{i,t-1}$	0.0255*** (0.000538)	0.0268*** (0.000936)	0.0236*** (0.000971)	0.0261*** (0.00106)	0.0252*** (0.00116)
R^2_{Adj}	0.0504	0.0555	0.0472	0.0481	0.0552
#Obs	1030111	260156	252786	245231	271938
Office FE	✓	✓	✓	✓	✓
Race, OccGrp FE	✓	✓	✓	✓	✓
Educ, Age, Year FE	✓	✓	✓	✓	✓

10% data, Offices with size less than 3 are excluded; Standard Errors are clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B

Appendix for Chapter 2

B.1 Data Cleaning Details

I follow the general approach in cleaning the data as in Bolton and de Figueiredo (2017). Since the dataset is very large, I take a conservative approach in data cleaning. In my analysis, I remove observations that are prone to error, such as an individual changed gender or race, missing service status and missing duty stations.

Appendix C

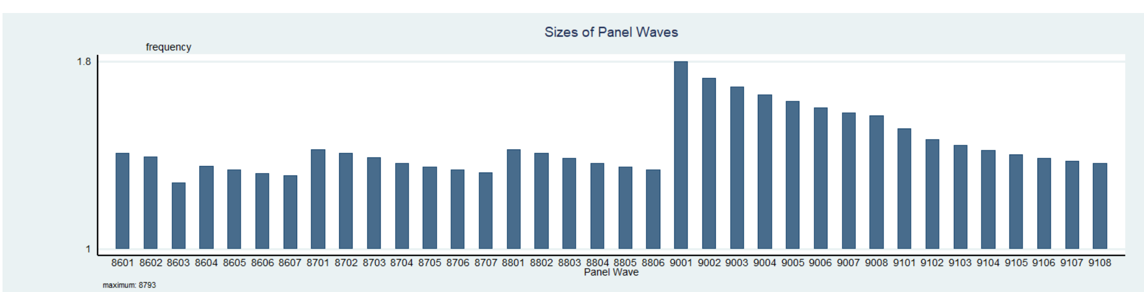
Appendix for Chapter 3

C.1 Data Cleaning Details

I follow the general approach in cleaning the data as in Barkowski (2014). the imputed Medicaid eligibility follows Currie and Gruber (1996a,b); Cutler and Gruber (1996a); Gruber and Yelowitz (1999); Gruber and Simon (2008), on the basis of observable data and detailed, state-level eligibility rules. We use the program developed and used by Gruber and Yelowitz (1999). For children, we impute the eligibility up to age of 20, which is the highest possible age a person could be eligible as a child. We define the female of reproductive age to be between age of 15 to 44, inclusive.

The following Figure C.1 depicts the sample sizes of each panel wave.

Figure C.1: **Sizes of Panel Waves**



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